Determinants of adoption of climate smart and sustainable coffee production practices and its impacts on coffee productivity

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Abstract

Global agricultural systems are increasingly getting exposed to unprecedented shocks emanating from climate change. Uganda, whose main export crop is coffee with the sector employing over 5 million people in farms and post-harvest processes, has seen its coffee experiencing declining productivity as a result of adverse effects of climate change. Continuation of this trend will see the livelihood of over 1.7 million smallholder coffee farming households placed under threat. Climate smart practices including cultural pests and disease control, soil fertility and water retention, and intensification have been promoted to be adopted in a stepwise approach as a measure against the negative impacts of these adverse climate events. However, limited empirical evidence exists to show the impacts of adopting these climate smart practices on coffee productivity. This study contributes to this gap by deploying a multinomial endogenous switching regression model to investigate the determinants of adoption of these climate smart and sustainable coffee production practices and its impacts on coffee productivity. The results revealed that farmers' education level, group membership, access to input dealers, information and credit significantly increased adoption of climate smart and sustainable coffee production practices. Sustainable yield increases are achieved when the recommended practices are adopted in combination and even higher yields are achieved when cultural pest and disease control practices are combined with either soil and water retention or intensification practices. The implication of this to policy is that climate smart practices should be promoted as combinations having cultural pest and disease control as one of the practices.

Key words: Climate-smart production; coffee productivity; treatment effects; endogeneity

1. Introduction

It is an increasing phenomenon for the global agricultural crop production systems to get exposed to unprecedented shocks emanating from climate change (IPCC, 2014). These shocks together with increasing global temperatures will result in changes in suitability for agricultural production (Fischer et al. 2002). Thus, presenting a huge threat to yield and welfare of farmers, especially smallholder farmers in Sub-Saharan Africa (SSA) whose livelihood strongly depends on agriculture (Oyetunde-Usman *et al.,* 2020). More so, coffee farmers are more susceptible to these climate changes and will be among the most affected given that coffee requires between three to five years to mature and a significant investment is required to plant and maintain it (Bro *et al.,* 2019).

Uganda is Africa's second largest coffee producer with 1.7 million smallholder coffee households, representing 10% of global coffee farms. Three to four million bags of coffee are produced annually, accounting for 18% of the country's annual exports (Bunn *et al.,* 2019). The sector employs over five million people, both in the farms and post-harvesting processes, remaining the primary source of income and livelihood for the poor rural inhabitants in over 30 districts and contributing substantial foreign exchange earnings over the decades (Verter *et al.,* 2015). Despite the enormous contribution of the crop to economic development of Uganda, coffee is experiencing declining levels of productivity, and this is of great concern among national and global stakeholders. It should be noted that in recent decades, the productive potential of the coffee-growing regions has become increasingly compromised by the impacts of climate change with many coffee production areas becoming drier and hotter (Donovan and Poole 2014). The implication of this is that productivity has kept on declining even with increases in production area. Bunn *et al.* (2019) revealed that the area cultivated with coffee in Uganda expanded by 50% since 1990, but productivity within the same period has been declining.

To address this mishap that is gradually crippling Uganda's coffee sector, research institutions, government development agencies and policy makers came up with numerous climate smart and sustainable coffee production practices to be promoted for use among coffee farmers (Bunn et al., 2019). Since variations in resource endowments among smallholder farmers could hinder efficient adoption of the proposed practices, it was recommended that such practices be broken down into four smaller, sequential, and incremental steps (also commonly referred to as the stepwise approach) to increase adoption. The first step constitutes low-cost practices, mainly routine and basic field management practices that ought to be practiced by every coffee farmer. This therefore implies that every farmer implementing only any or all of the practices under this step is a non-adopter. Costs increase in steps that follow and all individuals implementing practices under the subsequent steps are categorized as adopters (see table 1).

[Table 1 near here].

It was well thought out that through building up slowly, the farmer can obtain incremental increases in yields after each step, which may motivate them to re-invest part of the income to implement more practices of the next step to efficiently increase their yields (Bunn et al., 2019). Following this tremendous effort, this study utilizes a sample of 1231 coffee growing households that was obtained from the annual agricultural survey (2018/2019) data set collected by the Uganda

Bureau of Statistics to investigate (1) the drivers of adoption for the different climate smart and sustainable coffee production practices that have been promoted under the different steps and (2) assess the impact of adopting climate smart and sustainable production practices on coffee productivity. The two objectives were analyzed using the multinomial endogenous switching regression model. Key findings from the study indicate that the level of adoption of climate smart and sustainable coffee production practices was very low in Uganda and that access to credit, farmer group membership, access to input dealers, access to production information and education level of the farmer positively influenced adoption. With regard to the impact of adoption of the practices on coffee productivity, the findings from the study revealed that adoption of cultural pest and disease control in coffee production (C_1 S_0 I_0) resulted in the highest productivity (yield) increase for the farmer (110% yield increase). The findings from this investigation will provide input for government entities like the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) for the development of a National Coffee Sustainability Plan that is still nonexistent. Private sector organizations like Uganda Coffee Development Authority (UCDA), National Union of Coffee Agribusiness and Farm Enterprises (NUCAFE) and coffee cooperatives will pick out evidence-based strategies for successful scaling of climate-smart and sustainable coffee production practices. Overall, the findings will offer a clear strategic plan for supporting producers and promoting sustainable coffee production while aligning production in the country with the broader objectives of the SDGs such as poverty reduction and ensuring food and nutrition security.

The rest of the paper is structured as follows. first, we present the Conceptual/theoretical background to the paper, which is closely followed by the data section under which the statistical summaries are presented. The methods section comes in next after the data section and is immediately followed by the results and discussions section. Conclusion, Policy recommendations, Acknowledgments and references then proceed in order after the results section and lastly Tables are presented after the references section.

2. Conceptual/theoretical background

Agricultural production systems continue to suffer from the advancing effects of climate change. The coffee sector is one of the important sectors that has not been spared by this changing climate patterns. In Uganda for instance, about 25% of land that was deemed suitable for Arabica coffee has been lost due to climate change effects (Ovalle-Rivera et al., 2015). Likewise, coffee production is expected to reduce by 50%-75% due to loss of suitable land and decreasing yields (MWE, 2015). These forecasted effects accompanied by the increasingly high uncertainty around future changes of the climate in Uganda, have propelled stakeholders engaged in Uganda's coffee sector to promote climate smart agricultural practices as mitigation measures to the adverse effects of climate change on coffee production. In most cases, a stepwise approach has been proposed for adoption of such practices to ensure that they are feasible for even the resource constrained farmers (Bunn et al., 2019). However, it must be noted that in reality, farmers are often faced by overlapping constraints, such as weeds, pest, and disease infestations, and low soil fertility and declining crop productivity (Dorfman, 1996; Khanna, 2001; Moyo and Veeman, 2004). Which necessitates they adopt the promoted packages simultaneously as complements, substitutes, or supplements if they are to receive highest possible returns and build sustainable agricultural system that is more resilient to shocks related to climate change. Overall, although there is evidence that the promoted climate smart and sustainable coffee production practices play a great role in averting the negative impacts of climate change on coffee production, there exists a gap on the drivers of adoption of these practices and how they impact coffee productivity.

Numerous studies have been previously conducted to investigate the drivers of adoption of climate smart agricultural practices by farmers. At household level for instance, Kansiime et al. (2014) showed that perception of rainfall variability, gender of the head of household, household size, and access to output markets, significantly increased the probability of the farmer recording an adaptation measure. On the other hand, access to off-farm income, input markets, and location of the farmer negatively affect adoption of technologies. Ali. (2021), deployed a multivariate model to investigate the determinants of the choice climate-smart practices among farm households in Northern Togo. Results of his study showed that factors that influence households' choice of adaptation strategies include gender, household location, education level, family size, and allocated labor. Institutional factors including market access, access to credit, and extension services were also found to be key determinants in promoting the use of climate-smart practices. Oyetunde-Usman et al. (2020) employed multivariate probit and the ordered probit models to examine the determinants of adoption of multiple sustainable agricultural practices among smallholder farmers in Nigeria. Their empirical results showed that farmers' adoption of different SAPs and their intensity of use depend significantly on factors such as the age of household head, gender, education, household size, access to extension services, and household wealth status. Bro et al. (2017) used an ordered probit model to assess the determinants of adoption of sustainable production practices by coffee producers in northern Nicaragua. Their findings showed that coffee farmers who belong to cooperatives adopted sustainable practices at higher rates than non-members, and that the odds of adoption are higher for members than for non-members.

Ojoko et al. (2017) revealed that education, membership of a social group and access to credit were significant determinants of CSA adoption in Sokoto State in Nigeria. Akrofi-Atiotianti et al. (2018), while investigating CSA adoption among cocoa farmers in Ghana, found that age and location of farms, farmers' age, residential status and access to extension services influence CSA adoption in the cocoa farming system in Ghana. Aryal et al. (2018) studied the factors influencing the adoption of CSA practices by farmers in the Indo-Gangetic plains of India. Results of their study revealed that gender, education, social and economic capital, as well as farmers' experience of climate risks and access to extension services and training were key determinants of CSA adoption among the farmers. Zakaria et al. (2020). fitted an Endogenous-Switching Poisson regression model to determine the drivers of farmers' participation in climate change capacity building programmes and the concomitant effect of participation on adoption intensity of Climate Smart Agricultural Practices (CSAPs). The study found that participation in climate change capacity building training is endogenous and is positively influenced by farmers' access to agricultural extension services and membership of farmer-based organizations (FBOs). Consequently, participation in capacity building training, family labor, and agricultural insurance significantly influenced farmers' CSAPs adoption intensity. Abegunde et al. (2019) used a Generalized Ordered Logit Regression (gologit) model to analyze the determinants of the adoption of Climate-Smart Agricultural practices by small-scale farming households in South Africa. Results from their study showed that educational status, farm income, farming experience, size of farmland, contact with agricultural extension, exposure to media, agricultural production activity, membership of an agricultural association or group and the perception of the impact of climate change were found to be statistically significant and positively correlated with the level of CSA adoption. Furthermore, off-farm income and distance of farm to homestead were statistically significant but negatively correlated with the CSA level of adoption. The variation in the drivers of adoption of climate smart agricultural practices across the different studies reviewed herein is a clear indication of the heterogeneity that exists among farmers when making adoption decisions for the different climate smart packages that need to be investigated in order to inform wider uptake.

3. Data

This study made use of the Annual Agricultural Survey (2018/2019) dataset that was collected by Uganda Bureau of Statistics (UBOS) in close collaboration with the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) and Food and Agriculture Organization of the UN (FAO). The dataset from the AAS survey contains variables including farmer profiles, agricultural enterprises undertaken, agricultural inputs and sources, agricultural practices, access to information and other social amenities essential for agricultural production, which made it a good fit for the analysis conducted in this study.

To keep within the focus of the study, only data entries from households that ventured in or were engaged in coffee production at the time of the survey were filtered and considered for use during analysis. Key variables of interest identified and used for the analysis included use of irrigation, engagement in agroforestry, use of agricultural inputs like fertilizers, access to weather information, credit facilities, use of improved seeds and new varieties, access to nurseries, coffee yield, harvesting, post-harvest and marketing data, and any other practices around coffee farming. Socioeconomic variables related to age of household head, gender of household head, household size, land ownership status, formal education levels, production shocks faced like drought, hailstorms, pests and diseases, access to extension services, distance from a market in kilometers, among others were also considered. Full details of the variables used during the analysis and the sections under which they are recorded within the AAS dataset are summarized in the table 2 below.

[Table 2 near here].

Summary statistics for variables used in analysis

Table 3 shows the summary statistics for the variables used in analysis. Climate smart practices include: cultural control of pests & diseases (C), enhancement of soil fertility & water retention (S) or intensification (I), with subscript 1 referring to adoption and 0 otherwise. Generally, the results reveal that non-adopters (C_0 S_0 I_0) lag behind adopters with respect to most attributes. For instance, 16% of the farmers who adopted all the recommended practices (C_1 S_1 I_1) reported to have accessed agricultural loans compared to only 9% of the non-adopters. Similarly, 74% of the farmers who adopted all practices reported having access to input dealers/stores compared to only 45% of the non-adopters. Furthermore, 37% of the farmers who adopted all practices accessed agricultural production information compared to only 14% of the non-adopters. More farmers in the C_1 S_1 I_1 category belonged to farmer groups (34%) compared to only 12% of the non-adopters. However, farmers who adopted only intensification practices only (C_0 S_0 I_1) were approximately five years younger than both the non-adopters and full adopters (C_1 S_1 I_1). On the other hand, 77% of the households that did not adopt any practice (C_0 S_0 I_0) were male headed compared to only 66% of the households that adopted all practices. With regard to the region, the highest proportion of full adopters (76%) was in central Uganda while the highest proportion of non-adopters (42%) was found in the western region. This could be attributed to coffee being the main cash crop in the central region unlike the western region where banana is the major cash crop.

[Table 3 near here]

Proportion of farmers adopting different climate smart and sustainable practices

Table 4 presents the level of adoption of different climate smart and sustainable coffee production practices, including cultural control of pests & diseases (C), enhancement of soil fertility & water retention (S) or intensification (I) (with 1 = adoption and 0 otherwise). In total, a farmer had eight possible combinations of climate smart and sustainable coffee production practices from which to choose. The data shows that generally adoption of the related practices is still very low in Uganda. More specifically, 36% of the coffee farmers did not adopt any of the recommended practices (C_0 S_0 I_0) and about 46% of the farmers reported to have adopted at least one of the recommended practices (C_1 S_0 I_0, C_0 S_1 I_0 and C_0 S_0 I_1). Only 3% of the farmers adopted all the recommended practices (C_1 S_1 I_1).

[Table 4 near here].

4. Methods

In practice, assessing the impact of technologies and agricultural innovations involve randomly allocating participants into treatment (those receiving the intervention) and control groups (those not assigned to any intervention), a process referred to as a randomized control trial (RCT). The RCT impact assessment design is sufficient enough to provide unbiased treatment effect estimates especially when subjects are randomized. However, for most farm technologies and innovations, farmers endogenously self-select, and their adoption decisions are often influenced by unobserved factors that are somehow correlated with outcome variables (Khonje et al., 2018). In such instances, selection bias emanating from both observed and unobserved heterogeneity needs to be controlled if consistent estimates are to be obtained (Teklewold et al., 2013).

The propensity score matching (PSM) approach is one technique that has been widely used in impact evaluation literature to control for observable selection bias (Kassie et al., 2011; Linden, 2017). It offers the advantage of reduced selection bias by balancing the observed distribution of covariates across the treated and control groups. Use of the PSM approach has even been made better through incorporation of weighting mechanisms, including an IPW estimator that models the probability of treatment without any assumptions about the functional forms of the outcome model (Huber et al., 2010). However, such estimators become extremely unstable as the overlap assumption gets close to being violated and sensitive to misspecification of the propensity score model (Kikulwe et al., 2019). Doubly robust estimators such as the augmented inverse-probability-weighted (AIPW) estimator developed by Robins et al. (1994) are therefore used to improve the efficiency of IPW estimators. This is because AIPW has the potential to accommodate both the outcome regression model and the propensity score model to derive an estimator that remains consistent if either of the two models is correctly specified (Tan, 2010). A main setback for the propensity score matching method and its related model extensions like the IPW and AIPW is that they are only valid if the unconfoundedness and overlap assumptions are satisfied (Linden et al., 2015). Additionally, Abdulai (2016) and Jaleta et al. (2016) show that during simulation using these approaches, strong ignorability is assumed as a result, they cannot be used to correct selection bias arising from unobserved factors. Multinomial endogenous switching regression (MESR) models have been proposed in literature to account for the unobservables. MESR is based on a selection correction method that generates an inverse Mills ratio using the theory of truncated normal distribution and latent factor structure, respectively, to correct for selection bias associated with both observed and unobservables (Bourguignon et al., 2007). Based on the strengths of the MESR model, this paper therefore employs the multinomial endogenous switching regression model to investigate the determinants of adoption and impact of climate smart and sustainable coffee production practices on coffee yields in Uganda. The multinomial endogenous switching regression approach is a two-stage impact assessment procedure. The first stage models determinants of farmers' choice of climate smart coffee production practices using a multinomial logit model (MNL). The second stage models the impact of the chosen climate smart coffee production practices on the outcome under investigation (yield).

When operationalizing the multinomial endogenous switching regression model (MESR), we follow the utility maximization framework to model coffee farmers' decisions to adopt climate smart and sustainable coffee production practices. We defined non-adopter as those farmers who have only ventured in the normal/basic coffee management practices stipulated in step 1 (See table 1). Farmers implementing any of the activities specified in steps 2, 3 and 4 (cultural pest and disease control, soil fertility and water retention and intensification practices, respectively) or a combination are referred to as adopters of the climate smart coffee production practices. Following Asfaw et al. (2012) and Ghimire et al. (2015), we assume that each farmer's adoption decision is given by an underlying utility function, and the farmer makes a choice to adopt climate smart and sustainable coffee production practices based on maximization of expected utility. We further conceptualize that before adoption of sustainable coffee production practices in one or more steps, a household compares the net benefit of adopting or not adopting. The farmer only chooses to adopt a given set of practices in the next step if the net benefit/utility derived is greater than non-adoption or staying at the current step. This study assessed adoption by the numbers of steps adopted at household levels. The dependent variables in this study were discrete in nature taking the values j = 1, 2, 3…….8. With 1 representing the non-adopters and 2 to 8 representing adopters of climate smart coffee production practices either singly or in combination. With the dependent variables presented as discrete choice options, a multinomial logit model was opted for to conduct analysis on the determinants of adoption at each step. The model was specified as

$$U_{ij} = \beta_j X_i + \varepsilon_{ij} \quad (1)$$

Where U_{ij} is the utility farmer i derives from making choice j, X_i is a vector of explanatory variables that influence farmers' utility, β_j is a vector of parameters, and ε_{ij} is the error term. A farmer's choice of climate smart coffee production practice j with respect to any other alternatives is represented as follows:

$$\{1 \; if \; I_{ji} > \; max_{k \neq 1} \, (I_{ki}) \; or \; \eta_{1i} < 0 : \; for \; all \; k \; \neq j \; J \; if \; I_{ji} > \; max_{k \neq j} \, (I_{ki}) \; or \; \eta_{ji} < 0 \quad (2)$$

Equation 2 above indicates that the ι^{th} farmer will adopt package j only if it offers greater benefit (benefit/returns) compared to any other package available for selection $k \neq$ j

Within the multinomial model, assuming an independent and identically distributed error term the probability that an individual *i* will choose alternative *j* is thus specified as

$$Pr(choice = j) = \frac{exp(\beta_j X)}{\sum_j^n \; exp(\beta_j X)} \quad (3)$$

The impact of the climate smart coffee production practices on the target outcome (coffee yields) is estimated using the following regime equation

$$Regime\ 1: R_{1i} = \delta_1 Z_{1i} + w_{1i} \;\; if\ i = 1 \quad (4)$$

$$Regime\ J: R_{ji} = \delta_j Z_{ji} + w_{ji} \;\; if\ i = j, \quad j = 2, 3, \ldots, 8 \quad (5)$$

Where *R* is the coffee farmers' yield in regime *j, Z* is a set of household characteristics and other explanatory variables including access to credit, access to input dealers, distance to markets among others and *w* is the error term. The fact that there are higher chances of having unobserved correlation between first and second stage regression, means that w and ε are not independent. In this case, δ should therefore be estimated by including additional selection correction terms of alternative choices λ (Bourguignon et al., 2007). This equation can be written as follows

$$Regime\ 1: R_{1i} = \delta_1 Z_{1i} + \sigma_1 \lambda_{1i} + w_{1i} \;\; if\ i = 1 \quad (6)$$

$$Regime\ J: R_{ji} = \delta_j Z_{ji} + \sigma_j \lambda_{ji} + w_{ji} \;\; if\ i = j, \quad j = 2, 3, \ldots, 8 \quad (7)$$

Where λ is the inverse mills ratio predicted and computed from the probability estimates in equation (2), w is the error term with an expected value of 0, and σ is the covariance between u and ε. The estimates from equations 6 and 7 yield the counterfactual and treatment effects that are then used to compute the impact of climate smart coffee production practices on the target outcome, which is the coffee yield. The average treatment effects on the treated (ATT) are then computed following Kassie et al. (2015) and Khanal et al. (2020) as expressed below.

Coffee farmers who participated in *j* climate smart and sustainable coffee production practice (actual)

$$E[R_{ji} | I = J, \; Z_{ji}, \lambda_{ji}] = \delta_i Z_{ji} + \sigma_{j\varepsilon} \lambda_{ji} \quad (8)$$

Coffee farmers who did not participate in *j* climate smart and sustainable coffee production practice (actual)

$$E[R_{1i} | I = 1, \; Z_{1i}, \lambda_{1i}] = \delta_1 Z_{1i} + \sigma_{1\varepsilon} \lambda_{1i} \quad (9)$$

Coffee farmers who participated in *j* climate smart and sustainable coffee production practice had they decided not to participate in any climate smart and sustainable coffee production practice (counterfactual)

$$E[R_{1i} | I = J, \; Z_{ji}, \lambda_{ji}] = \delta_1 Z_{ji} + \sigma_{1\varepsilon} \lambda_{ji} \quad (10)$$

Coffee farmers who did not participate in *j* climate smart and sustainable coffee production practice had they decided to participate (counterfactual)

$$E\left[R_{ji}|I = 1,\ Z_{1i}, \lambda_{1i}\right] = \delta_1 Z_{1i} + \sigma_{j\varepsilon}\lambda_{1i} \tag{11}$$

The average effect of involvement in any of the climate smart and sustainable coffee production practices on coffee productivity (yields) of the farmers (ATT) is then computed as the difference between equation (8) and equation (10) which can be written as:

$$ATT = E\left[R_{ji}|I = J,\ Z_{ji}, \lambda_{ji}\right] - E\left[R_{1i}|I = J,\ Z_{ji}, \lambda_{ji}\right] = Z_{ji}\left(\delta_j - \delta_1\right) + \lambda_{ji}\left(\sigma_j - \sigma_1\right) \tag{12}$$

5. Results and Discussion

5.1. Determinants of adoption of climate smart and sustainable coffee management practices.

Table 5 presents results from the multinomial logit model. The base category is non-adoption (C_0 S_0 I_0) to which results are compared. The results show that the estimated coefficients differ substantially across the alternative packages. Age of the household head was found to have a negative impact on the adoption of a combination of cultural control of pests & diseases, and enhancement of soil fertility & water retention (C_1 S_1 I_0), and the combination of all recommended practices (C_1 S_1 I_1). This could be attributed to the fact that implementation of some of these practices requires physical strength which reduces with age. This contradicts findings by Ntshangase et al. (2017) and Massresha et al. (2021) who found a positive relationship between age and adoption of agricultural technologies. Additionally, there is a strong correlation between the occupation of household head and adoption of intensification practices only (C_0 S_0 I_1) whereby agriculture as the main occupation increases the probability of venturing into intensification practices only. This is possible because such households solely rely on agriculture for income and food security and thus are pushed to adopt agricultural intensification to maintain higher levels of production. Additionally, access to agricultural loans was found to increase the likelihood of adoption of C_1 S_0 I_1 practices. This could be attributed to the high investment costs associated with intensification, which is part of the practices in the combination, thus necessitating external financing through borrowing. This finding supports that of Abdallai (2016) who noted that access to credit positively influenced adoption of conservation agriculture technologies and Nakano and Magezi (2020) who found a positive relationship between credit access and fertilizer use among households with no access to irrigation water facilities. The results further reveal that intensification practices are strongly correlated with access to agricultural input dealers/stores. Access input dealers increased the likelihood of adopting either a combination of intensification practices and soil fertility enhancement & water retention (C_0 S_1 I_1) practices or adoption of all recommended practices (C_1 S_1 I_1). This supports earlier research that revealed that input dealers offer farmers with detailed information about different inputs which positively impacts adoption (Dar et al., 2020). Adoption of C_1 S_1 I_1 practices was also more common among households that had accessed agricultural production information, though it reduced the likelihood of venturing in C_1 S_0 I_0 practices only. Studies show that access to production information enables farmers to make more informed decisions thus increasing the possibilities of adopting more innovations while cultural control practices are generally known considering that they have been in place for a prolonged period of time (Walgenbach, 2018; Freeman and Qin, 2020).

Membership to farmer groups also increased the likelihood of adopting C_1 S_0 I_0 and C_1 S_0 I_1 practices. This could possibly be attributed to increased knowledge sharing among group members (Awotide et al., 2016). Furthermore, occurrence of drought increased the likelihood of adopting the C_0 S_1 I_0 practices, but reduced the likelihood of adopting all the recommended practices (C_1 S_1 I_1). Occurrence of prolonged droughts can potentially lead to drying and ultimately death of the coffee plant, creating a greater need for soil and water conservation in place of adopting all recommended practices which are unaffordable to most smallholder farmers (Namenya et al., 2014;). On the other hand, more educated farmers are more likely to adopt all recommended practices (C_1 S_1 I_1), but are less likely to adopt C_1 S_0 I_0 practices only. Higher education level possibly enables a farmer to internalize agricultural information faster (Kasirye, 2013; Awotide et al., 2016)

Households in the central region are also more likely to adopt C_1 S_0 I_1 practices, but less likely to adopt C_1 S_0 I_0, C_0 S_1 I_0 and C_0 S_0 I_1 practices only. Households in the western region were more likely to adopt C_0 S_0 I_1, c_1 S_1 I_0 and C_1 S_0 I_1 practices but reduced the likelihood of adopting C_1 S_0 I_0 and C_0 S_1 I_0 practices only. This could be attributed to coffee being the major cash crop in the central region, yet the region has become drier overtime unlike in western region where bananas are the major cash crop (Lindrio, 2021; UCDA, 2021). Finally, the occurrence of heavy rains reduced the likelihood of adopting C_1 S_0 I_0 practices, but increased the likelihood of adopting C_0 S_0 I_1 and C_1 S_1 I_1 practices.

[Table 5 near here]

5.2. Average treatment effects of vertical coordination mechanisms on farm performance outcomes

Table 6 below presents estimates of the average treatment effect on the treated (ATT) of climate smart and sustainable coffee production practices on coffee productivity (yield) generated using a multinomial endogenous switching regression model. The variables accessed agricultural loans and traditional coffee were used as instruments for adoption (Major_dependent) in the model. A test of endogeneity was conducted on the adoption variable (Major_dependent) and a significant result was obtained ($F(1, 1216) = 6.7178$, $p = .009$) thus satisfying the endogeneity assumption for the regression model. Instrument validity, specifically tests for instrument strength and over identification, was further conducted. Results from the tests revealed that the associated F-statistic for the instruments in the first-stage regression was 43.00 which is higher than the strictest critical value of 16.38 reflected by Stock and Yogo (2005), thus indicating that the instruments are relevant and not weak. The Sargan and Basmann test for overidentifying restrictions was also fulfilled, yielding chi2(1) = 0.003746 ($p = 0.95$) and chi2(1) = 0.003701 ($p = 0.95$), respectively.

Overall, the results of the ATT show that relative to the non-adopters, if adopted singly, participation in cultural pest and disease control in coffee production (C_1 S_0 I_0) results in the highest productivity (yield) increase for the farmer (110% yield increase). This is closely followed by soil fertility and water retention (C_0 S_1 I_0) at 56% yield increase and lastly intensification practices (C_0 S_0 I_1) at 52%. When adoption of the practices is carried out in combination, relative to the non-adopters, all possible combinations with cultural pest and disease control inclusive resulted in a higher percentage yield increase compared to combinations without it.

[Table 6 near here].

6.0 Conclusion and policy recommendation

6.1 Conclusion

Climate smart practices have been promoted to enhance sustainable coffee production in Uganda amidst an environment faced with increasing adverse effects of climate change. There is limited information on adoption of single or multiple combination sets of these climate smart practices and their impacts on coffee productivity. The results of this study suggest that older farmers are less likely to adopt climate smart practices. In particular, regression results revealed that as farmers get older, their likelihood of adopting a combination of cultural control of pests & diseases and soil fertility & water retention (C_1 S_1 I_0) and the combination of all recommended practices (C_1 S_1 I_1) significantly reduced. The results further revealed that access to agricultural loans, information and input dealers increased the likelihood of adopting climate smart coffee production practices. Similarly, membership to farmer groups increased the probability of adopting C_1 S_0 I_0 and C_1 S_0 I_1 practices. On the other hand, highly educated farmers were more likely to adopt all the recommended climate smart practices. Regarding yields, the results revealed that more yields were obtained if the practices were adopted as a combination with cultural pest and disease control as one of the practices in that given combination.

6.2 Recommendations

From the results of this study, it is evident that credit access plays a key role in the adoption of climate smart coffee production practices but only a small proportion of farmers reported to have received a line of credit. There is a need to develop policies that will make loans from financial institutions more affordable and accessible to small scale farmers. Governments should promote adoption of climate smart coffee production practices by reducing financial resource constraints such as taxes on irrigation equipment or procure needed equipment at sub-county level so that farmers can borrow and use it at a subsidized cost. The results further revealed that farmer group membership increased adoption of climate smart practices. Government through its programs such as operation wealth creation needs to empower farmers to form cooperatives to increase information flow and also make credit access easier to group members. To encourage mass uptake of the practices, there is need to introduce a certification plan for all coffee that is produced following the sustainable practices and offer price premium for such coffee to motivate farmers' participation. Finally, climate smart practices should be promoted as combinations having cultural pest and disease control as one of the practices if higher returns to coffee productivity are to be achieved.

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Table 1: Intensification steps and sustainable coffee production practices under each step

	Step 1	Step 2	Step 3	Step 4
Practices	**Basic management practices** (Pruning, Weeding, use traditional seeds, and intercropping)	**Cultural control of pests & diseases** (Spraying, (Improved and tolerant seedlings)	**Enhancement of soil fertility & water retention** (Mulching, organic fertilizer, afforestation, zero or no tillage and manure application	**Intensification** (Pesticides, in-organic fertilizers, and irrigation)

Table 2. Summary of variables used for econometric modelling and analysis.

No	Data needed for the analysis	Sub-section under which they fall in the AAS questionnaire
1	Demographic variables	Household roaster (section 5.2)
2	Participation in agroforestry	Enterprise roaster (section 4.3)
3	Land ownership type and acreage owned	Parcel roaster (4.4)
4	Land preparation mechanism (tillage type)	Plot roaster (section 4.5)
5	Area under coffee production	Plot roaster (section 4.5)
6	Crop type coffee	Crop roaster (section 4.6)
7	Seed type used (local, improved)	Crop roaster (section 4.6)
8	Coffee yields and revenue (Income from coffee)	Crop production and disposition (section 5.3)
9	Inputs used for coffee production (Fertilizer, pesticides, herbicides etc)	Agricultural inputs (Section 5.4)
10	Coffee management/ agricultural activities undertaken (Mulching, spraying, pruning, weeding, irrigation)	Agricultural activities and costs (section 5.5)
11	Access to agricultural information (weather, markets, crop varieties etc)	Sources of agricultural information (section 5.10)
12	Access and proximity to key facilities	Access to facilities (Section 5.11)
13	Ownership of storage facilities	Storage facilities (section 5.13)
14	Credit access	Access to credit (section 5.14)
15	Exposure to agricultural shocks	Shocks and food security (section 5.16)
16	Access to extension	Extension services (section 5.17)

Table 3. Summary statistics of variables used in analysis

	All Sample	Mean values for climate smart and sustainable practices								F/Chi2 Value
		$C_0 S_0 I_0$	$C_1 S_0 I_0$	$C_0 S_1 I_0$	$C_0 S_0 I_1$	$C_1 S_1 I_0$	$C_1 S_0 I_1$	$C_0 S_1 I_1$	$C_1 S_1 I_1$	
Age of household head (years)	48.98 (12.47)	49.87 (12.72)	48.92 (12.73)	49.27 (12 .37)	44.12 (12.77)	48.99 (11.60)	47.67 (11.64)	43.50 (11.71)	49.42 (11.12)	2.84***
Male-headed household (%)	78.64	77.43	76.85	79.09	97.50	77.06	76.19	87.50	65.79	15.69**
Married household head (%)	76.69	75.40	75.00	77.40	97.50	75.23	71.43	78.57	71.05	11.63
Agriculture as the main occupation (%)	80.58	81.26	81.48	79.09	87.50	84.40	80.95	76.79	73.68	4.70
Accessed agricultural loan (%)	12.43	8.80	8.33	12.98	17.50	23.85	23.81	12.50	15.79 |	24.03***
Has access to agricultural input dealers/store (%)	52.32	45.37	54.63	50.48	65.00	57.80	85.71	69.64	73.68	36.33***
Accessed production information (%)	18.44	13.54	12.04	18.75	25.00	24.77	23.81	35.71	36.84	34.15***
Cultivated land (Hectares)	0.23 (0.31)	0.19 (0.29)	0.20 (0.27)	0.21 (0.26)	0.26 (0.23)	0.34 (0.42)	0.42 (0.35)	0.31 (0.35)	0.46 (0.56	19.00***
Member of Farmer group (%)	14.70	11.74	9.26	15.38	12.50	22.02	19.05	16.07	34.21	22.55***
Was affected by hailstorms	7.07	7.00	1.85	7.69	17.50	7.34	9.52	5.36	5.26	11.99
Household size	6.45 (2.70)	6.26 (2.74)	6.15 (2.57)	6.49 (2.58)	6.66 (2.70)	6.99 (2.88)	6.38 (3.23)	6.80 (2.64)	6.84 (3.33)	1.38
Education level of household head %										
Had nursery or no education	13.57	16.48	14.81	13.70	5.00	11.93	9.52	3.57	5.26	29.84*
Attained primary level education	59.95	60.27	51.85	61.06	65.00	62.39	52.38	55.36	65.79	
Attained secondary level education	23.48	20.77	29.63	22.84	22.50	21.10	38.10	37.50	23.68	
Education level above secondary	3.01	2.48	3.70	2.40	7.50	4.59	0.00	3.57	5.26	
Region %										
Central	33.39	25.28	33.33	29.81	37.50	55.96	66.67	35.71	76.32	
Eastern	21.77	30.70	21.30	15.63	37.50	5.50	9.52	30.36	10.53	144.53***
Western	43.87	41.53	45.37	54.33	25.00	38.53	23.81	33.93	13.16	
Northern	0.97	2.48	0.00	0.24	0.00	0.00	0.00	0.00	0.00	
Yields (tons/hectare)	0.86 (1.08)	0.66 (0.70)	0.67 (0.70)	1.02 (1.30)	1.02 (1.03)	0.78 (1.11)	0.70 (0.76)	1.45 (1.64)	1.25 (1.38)	7.59***
Number of observations	**1231**									

Note: values in parentheses are standard errors. ***, **, & * represent statistical significance at 1%, 5%, and10%, respectively

Table 4. Climate smart and sustainable coffee production practice combinations adopted by farmers

Choice (j)	Binary triplet (package)	Cultural control of pests & diseases (C)		Enhancement of soil fertility & water retention (S)		Intensification (I)		Frequency	%
		C_1	C_0	S_1	S_0	I_1	I_0		
1	C_0 S_0 I_0		X		X		X	443	36
2	C_1 S_0 I_0	X			X		X	108	9
3	C_0 S_1 I_0		X	X			X	416	34
4	C_0 S_0 I_1		X		X	X		40	3
5	C_1 S_1 I_0	X		X			X	109	9
6	C_1 S_0 I_1	X			X	X		21	2
7	C_0 S_1 I_1		X	X		X		56	4
8	C_1 S_1 I_1	X		X		X		38	3

Note: The binary triplet represents the possible climate smart and sustainable coffee production practice combinations. Each element in the triplet is a binary variable for a climate smart and sustainable practice.

Table 5. Marginal effects for determinants of Adoption of climate smart and sustainable practices

Variable	$C_1 S_0 I_0$	$C_0 S_1 I_0$	$C_0 S_0 I_1$	$C_1 S_1 I_0$	$C_1 S_0 I_1$	$C_0 S_1 I_1$	$C_1 S_1 I_1$
Age of household head (years)	0.001	0.000	0.001	-0.001**	-0.000	-0.000	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Accessed agricultural loans (%)	-0.05	0.03	0.02	-0.02	0.04**	0.01	-0.01
	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.02)
Agriculture as main occupation (%)	0.01	-0.02	-0.02	0.01	0.02	-0.001	0.000
	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.009)	(0.01)
Was affected by drought (%)	-0.002	0.02*	0.03	0.01	-0.02	0.005	-0.03**
	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)	(0.008)	(0.02)
Has access to agricultural input dealers/store (%)	-0.04	-0.004	-0.01	0.01	-0.01	0.02**	0.02*
	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Accessed production information (%)	-0.08**	-0.02	0.02	0.01	0.02	0.001	0.03**
	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.009)	(0.01)
Cultivated land (Hectares)	-0.08	-0.05**	0.01	0.02	0.03	0.01*	0.04**
	(0.05)	(0.02)	(0.05)	(0.02)	(0.02)	(0.01)	(0.02)
Member of Farmer group (%)	-0.07*	-0.02	0.03	-0.01	0.03*	0.004	0.002
	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.009)	(0.02)
Was affected by heavy rains (%)	-0.25***	-0.04	0.17***	0.02	0.04	0.01	0.04**
	(0.05)	(0.03)	(0.05)	(0.01)	(0.03)	(0.01)	(0.02)
Household size	-0.003	-0.003	-0.001	0.000	-0.01**	-0.001	0.001
	(0.005)	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
Education level of household head	-0.04*	0.01	0.003	0.01	-0.004	0.003	0.02*
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.006)	(0.01)
Planted traditional coffee (%)	-2.04	0.16	2.19	0.21	-0.21	-0.06	0.26
	(96.30)	(2.01)	(126.34)	(57.74)	(4.84)	(1.81)	(60.24)
Central	-0.18***	-0.08***	0.16***	-0.01	0.07***	0.009	-0.01
	(0.03)	(0.02)	(0.04)	(0.01)	(0.03)	(0.01)	(0.01)
Western	-0.16***	-0.03*	0.22***	-0.03**	0.05**	0.0001	-0.02
	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)

Table 6. Average treatment effect of Climate smart and sustainable coffee production practices on coffee productivity (Yield)

Technology combination	Actual outcome	Counterfactual outcome	ATT	t-value	% Change in yield
$C_1 S_0 I_0$	0.67(0.03)	0.32(0.12)	0.35	2.77***	109.68
$C_0 S_1 I_0$	1.02(0.02)	0.65(0.01)	0.36	13.69***	55.81
$C_0 S_0 I_1$	1.02(0.11)	0.67(0.04)	0.35	2.88***	51.62
$C_1 S_1 I_0$	0.78(0.04)	-0.59(0.11)	1.37	11.48***	-231.57
$C_1 S_0 I_1$	0.70(0.17)	-0.72(0.33)	1.42	3.89***	-197.41
$C_0 S_1 I_1$	1.45(0.18)	0.69(0.04)	0.76	4.20***	109.42
$C_1 S_1 I_1$	-0.18(0.18)	-0.18(0.18)	0.00	0.00	0.00