INTERNATIONAL CONFERENCE OF AGRICULTURAL ECONOMISTS
ICAE
29th | Milan Italy 2015
UNIVERSITÀ DEGLI STUDI DI MILANO AUGUST 8 - 14
AGRICULTURE IN AN INTERCONNECTED WORLD

Impact of improved cassava varieties' adoption on farmers' incomes in Rural Ghana

Patricia Pinamang Acheampong[1*] *and Victor Owusu*[2]

[1]Socio-Economics Section
CSIR- Crops Research Institute, Ghana
ppacheampong@gmail.com
[2]Department of Agricultural Economics, Agribusiness and Extension
Kwame Nkrumah University of Science and Technology, Ghana
vowusu.agric@knust.edu.gh

Abstract

Using data from 450 cassava farmers from three districts, the paper uses a non-parametric propensity score matching (PSM) technique to investigate the impact on men and women farmers' incomes by adopting improved cassava varieties. The Average treatment effect (ATT) estimates suggested that participation in improved cassava varieties increased total crop incomes of women by ₵3173 (USD 1823) whilst that of men was increased by ₵149 (USD 86) per hectare. The findings offer justification for sustained public investment in cassava research and dissemination in Ghana.

Keywords: Improved cassava variety, impact, income, women, propensity score matching, Ghana
JEL codes:

1. Introduction

Ghana's agriculture is recognized to have a greater impact on poverty reduction than other sectors (MOFA, 2007) as it employs the majority of the working force. The agricultural sector is dominated by staple crops (MOFA, 2013). Amongst the staple crops in Ghana cassava is particularly important for farmers as it guarantees good yields even in harsh conditions. Due to cassava's importance a lot of attention has been paid to its developments and disseminations. These efforts have led to the official releases of 18 improved cassava varieties in Ghana by the Council for Scientific and Industrial Research and the public Universities, which are early maturing and high yielding, and also able to tolerate biotic and abiotic stresses. The underlying objectives of breeding and releases of new varieties are to increase food security and improve incomes of resource poor farmers. Cassava in particular has been identified as a single commodity that could generate desired economic growth, fight poverty and improve food security in Ghana (Nweke, 2004; Al-Hassan and Daio, 2007). Improved agricultural technology is believed to lead to poverty alleviation through positive effects on consumers' food prices, producers' incomes, and labourers' wage incomes (Irz et al., 2001; Diao et al., 2007). There are direct and indirect effects of agricultural technology on poverty, however evidences from many countries (de Janvry and Sadoulet, 2002), suggest the direct poverty alleviation impacts of agricultural technology are more important than the indirect effects. Important to the development of improved technologies and release of high yielding varieties are to reduce hunger, malnutrition, poverty and increase the incomes of poor people living in marginal areas (Irz et al., 2001). DFID (2003) and Irz et al. (2001) report that a 1 percent increase in agricultural productivity reduces the percentage of poor people living on less than 1 dollar a day by between 0.6 and 2 percent and no other economic activity generates the same benefit for the poor.

Although Ghana is the third largest producer of cassava in Africa and the Ghanaian farmers rely on the crop for consumption and income generation (MOFA, 2013), empirical evidence on its impact on smallholders' income is hard to find. Impact of improved cassava varieties adoption on smallhoder farmers' incomes is carried out in this study in order to show evidence that farmers benefit from growing improved cassava varieties so as to justify the continuous investment in its development and dissemination. The paper uses the non-parametric propensity score matching analyses in pursuance of whether adopting an improved modern cassava technology causes resource-poor farmers to improve their incomes and thereby improve livelihoods. This is a matching method to make comparison between those who have adopted and those who have not adopted and to draw conclusions based only on those who have adopted the improve cassava varieties. The welfare gains of adoption have mostly been assessed through non experimental means which have the problem of selection. It is impossible to observe those farmers who have adopted improved varieties have they not adopted them. If one could observe the same farmer at the same point in time, with and without the improved variety, this would effectively account for any observed or unobserved factors or any selection problem (Ravallion, 2005; Gilligan *et al.*, 2008). However, this ideal case does not exist in reality. In experimental methods, the selection problem is tackled by randomly assigning improved seeds to treatment and control groups which guarantees that the welfare outcome observed on the control households that adopt improved technology are statistically representative of what would have occurred without adoption. However, improved technology is not randomly distributed to the two groups of the households (adopters and non adopters), but rather the households themselves deciding to adopt or not to adopt based on the information they have.

The estimation of impact of adopting improved agricultural technologies that results from the simple difference between adopters and non adopters fail to properly control for potential differences between the technology adopters and non-adopters (Nabasirye *et al*.,2012). Rahman (1999) and Mendola (2007) note the difficulty in drawing conclusions from such accounts. As a result, in the absence of random selection of farmers in the adoption of improved cassava varieties, simple comparisons of average incomes obtained between adopters and non-adopters are likely to give upward bias estimates of the impact of adoption (Kassie *et al*., 2010). Accounting for selection bais has been a problem in most improved cassava varieties impact assessment studies in Africa. Most studies (Nweke, 2004; Omonona *et al*., 2006) have used the before and after technique which often gives bias results due to assumption that the change is only attributed to the programme or the intervention. This paper accounts for the true welfare effect of improved cassava adoption by controlling for the role of selection problem on adoption decisions.

The rest of the paper is organised as follows. Section 2 explores the theoretical and empirical frameworks of agricultural technology impact assessment, and the propensity score and average treatment effects. Sections 3 present the results and discussion. Finally, in section 4 conclusions and policy implications are provided

2.1. Conceptual Framework and empirical model

The estimation of impact of adopting improved agricultural technologies that results from the simple difference between adopters and non adopters fail to properly control for potential differences between the technology adopters and non-adopters (Nabasirye *et al*., 2012). Rahman (1999) and Mendola (2007) note the difficulty in drawing conclusions from such accounts. As mentioned early on, farmers choose to adopt or not adopt a given technology, depending on their expectations, objectives, and observable and unobservable characteristics. This is referred to as self-selection. Therefore simple comparison of adopters with non-adopters tends to overestimate the impact of the technology on incomes obtained. There are adopters and non-adopters of improved cassava varieties. The counterfactual is what would have happened to those farmers who, in fact, adopted improved cassava varieties, had they not adopted the technology. Therefore, the specific interest is to know what would have happened to the adopters, had they not adopted the technology. The key assumption is that individuals selected into treatment and non-treatment (control) groups have potential outcomes in both states, the one in which they are observed and the one in which they are not observed (Winship and Morgan, 1999).

Let A = 1 denote the state when the *it*h farmer adopts improved cassava variety, and A = 0 denote the state when he does not adopt improved cassava variety. Let Yi denote the actual observed outcome of individual farmer *i*. Then Y_{1i} is the outcome of *ith* farmer when he adopts the technology and Y_{0i} is the outcome if the farmer does not adopt the technology. The outcomes for the *ith* farmer can be defined as:

$$Y_1 = \gamma_1 \mathrm{X} + u_1 \qquad \textit{and}$$
$$Y_0 = \gamma_0 \mathrm{X} + u_0 \qquad (1)$$

where X is a vector of observed covariates, and u_1 and u_0 are unobserved random error terms with the assumption that $u_1 \neq u_0$ and the effect of choosing adoption versus no adoption is given as ($Y_1 - Y_0$). Following Heckman *et al*. (1998), the outcome equation for observed *Y*, conditional on treatment participation, may be written as a switching regression:

$$
\begin{aligned}
Y &= AY_1 + (1-A)Y_0 \\
&= \gamma_0 + A(\gamma_1 - \gamma_0 + u_1 - u_0) + u_0 \\
&= \gamma_0 + A(\gamma_1 - \gamma_0) + \left[A(u_1 - u_0) + u_0\right]
\end{aligned}
\tag{2}
$$

In reduced form, Eq. (2) can be rewritten as a standard regression model:

$$Y = \beta_0 + \beta_1 A + u \tag{3}$$

2.2. The propensity score matching and the Average treatment effect

The treatment effect, ($Y_1 - Y_0$) cannot be estimated using the model in Eq. (3) due to the strong potential of selection bias, thus turning to PSM to determine the average treatment effect on the treated farmers (ATT). That is, the causal effect of adoption of improved cassava varieties on incomes and on food security. For a given adopter, consider both the observed mean income under the condition of adoption of the technology as E (Y_1 |A= 1) and the unobserved (hypothetical) mean income that the adopter would have realized had they not adopted improved cassava variety as E (Y_0 |A = 1). Also, for a given non-adopter, consider the observed mean income under the condition of non-adoption of the technology as E (Y_0 |A = 0) and the unobserved (hypothetical) mean income that the non-adopter would have realized had they indeed adopted improved cassava variety as E (Y_1|A = 0). Here, E is the expectation operator.

According to Rosenbaum and Rubin (1983) the parameter of interest is the ATT, which is written as:

$$
\begin{aligned}
ATT &= E(Y_1 - Y_0 / A = 1) \\
&= E(Y_1 / A = 1) - E(Y_0 / A = 1)
\end{aligned}
\tag{4}
$$

In impact evaluation the interest is not in E (Y_0 |A = 0), but in E (Y_0 |A = 1). Therefore, PSM uses balancing scores to extract the observed mean income of those non-adopters who are most similar in observed characteristics to the adopters. That is, it uses E (Y_0|A = 0) to estimate the counterfactual, E (Y_0 |A = 1) (Nabasirye et al., 2012). Estimation for the true parameter requires that:

$$E(Y_0 / A = 1) - E(Y_0 / A = 0) = 0 \tag{5}$$

This ensures that the ATT is free of self-selection bias. To fulfil the condition in Eq. (5), PSM must satisfy two assumptions: conditional independence and common support. The conditional independence assumption (also known as exogeneity) requires that the value of the outcome variable is independent of the treatment state, given the values of some observable variables (Rosenbaum and Rubin, 1983). This means the selection into the treatment group is solely based on observable characteristics. The orthogonality condition expressed in Eq. (6) says that the values of the outcome variables Y_{1i} and Y_{0i} are independent of the treatment state (A), given the values of the observable variables in X.

$$Y_{1i}, Y_{0i} \perp A / X \tag{6}$$

Any systematic effect of treatment on the outcome variable (in this case income) can be entirely explained in terms of these observables. Thus, the differences in unobservable characteristics between the treated and untreated groups conditional on X are assumed to be random.

A second assumption which is the common support states that the average treatment effect for the treated (ATT) is only defined within the region of common support. This assumption ensures that persons with the same X values have a positive probability of being both participants and nonparticipants (Heckman et al., 1997). Nabasirye et al. (2012) note that the common support assumption is needed since matching on every covariate is difficult when there are many covariates. PSM solves this problem by estimating the propensity score which is given as: $P_{(X)} = P_r\left(\mathrm{A} = 1 / X\right)$ (Rosenbaum and Rubin, 1985). This is the conditional probability that the *ith* farmer will adopt improved cassava variety, conditional on the observed characteristics in vector X. Given that every individual has a positive probability of being both an adopter and non-adopter, and thus ruling out perfect predictability, the common support (overlap) condition implies that

$$0 < P_r\left(A = 1 / X\right) < 1 \tag{7}$$

These two conditions give the strong ignorability of treatment assumption that allows the use the PSM estimator (Nabasirye et al., 2012). This implies;

$$E\left(Y_0 / A = 1, P\left(X\right)\right) = E(Y_0 / A = 0, P\left(X\right)) \tag{8}$$

Then, according to Rosenbaum and Rubin (1985), the ATT can be written as**:**

$$\begin{aligned}
ATT &= E\left(Y_1 - Y_0 / A = 1\right) \qquad (9)\\
&= E\left[E\left(Y_1 - Y_0 / A = 1, P(X)\right)\right]\\
&= E\left[E\left(Y_1 / A = 1, P(X)\right) - E\left(Y_0 / A = 1, P(X) / A = 1\right)\right]\\
&= E\left[E\left(Y_1 / A = 1, P(X)\right) - E\left(Y_0 / A = 0, P(X) = 1\right)\right]
\end{aligned}$$

Where the outer expectations are over the distribution of Pr (A = 1|X).

A number of proposed methods are available to deal with matching similar adopters and non adopters. The methods differ from each other with respect to the way they select the control units that are matched to the treated, and with respect to the weights they attribute to the selected controls when estimating the counterfactual outcome of the treated. The commonly used approaches are the nearest neighbour matching and kernel-based matching methods (Becerril and Abdulai, 2009). The nearest neighbour method consists of matching each treated individual with the control individual that has the closest propensity score. It can be applied with or without replacement in the non participants units. Matching with replacement results in bias reduction since each treatment group can be matched to the nearest comparison group as a result of a reduction in the propensity score distance (Owusu *et al*., 2011). In the kernel-based method, all participants are matched with a weighted average of all non participants, using weights that are inversely proportional to the distance between the propensity scores of participants and non participants groups (Becker and Ichino, 2002). The most common approach is to use the normal distribution (with a mean of zero) as a kernel, where the weight attached to a particular comparison group is proportional to the frequency of the distribution for the difference in scores observed (Bryson et al., 2002). The choice of a specific method depends on the data in question, and in particular on the degree of overlap between the treatment and comparison groups in terms of the propensity score. When there is substantial overlap in the distribution of the propensity score between the comparison and treatment groups, most of the matching algorithms yield similar results (Dehejia and Wahba, 2002). However, in this study the nearest neighbour matching technique is used.

The analysis is based only on the propensity score and not on all covariates and thus there is the need to check if the matching procedure is able to balance the distribution of the relevant variables in the participants and nonparticipants groups. The basic idea is to compare the situation before and after matching and then check if there is any remaining differences after conditioning on the propensity score (Caliendo and Kopeinig, 2008).This is achieved by re-estimating propensity score on the matched sample only on adopters and matched non adopters and then comparing the pseudo-R^2's before and after matching(Sianesi, 2004). The pseudo-R^2 is supposed to indicate how well the regressors X explain the adoption probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore, pseudo-R^2 should be fairly low. The test should not be rejected before, but should be rejected after matching.

Matching method is based on the conditional independence or unconfoundedness assumption (CIA), which states that evaluator, should observe all variables simultaneously influencing the participation decision and outcome variables. This assumption is intrinsically non-testable because the data are uninformative about the distribution of the untreated outcome for treated units and *vice versa* (Becker and Caliendo, 2007). In order to estimate the extent to which such selection on unobservable covariates may bias the inferences; this study employed the Rosenbaum bounds sensitivity analysis to determine how strongly a non-measured variable must influence the selection process so that it could undermine the implications of the matching analysis (Rosenbaum, 2002). If there is a certain unobserved variable of concern that affects the selection process then the probability of treatment is:

$$P(X) = P_r\left(A = 1 / X, u\right) = F\left(\beta X + \gamma u\right) \qquad (10)$$

where X is a vector of all observed covariates and u represents the unobserved variable affecting assignment to treatment; γ is the effect of u on the treatment probability. If the estimator is free of hidden bias, γ is equal to zero and the participation probability is solely determined by X (Nabasirye *et al*., 2012). However, if there is hidden bias, two individuals with the same observed covariates can have different chances of adopting improved cassava variety. Rosenbaum (2002) proposes using Rosenbaum bounding approach in order to check the sensitivity of the estimated ATT with respect to deviation from the CIA. Comparison of the Rosenbaum bounds on treatment effects at different levels of gamma can assess the strength that unmeasured covariates must have in order for the estimated treatment effects from propensity score matching to have arisen purely through non-random assignment. The Rosenbaum bound at each value of gamma is the point at which hidden bias causes us to question the findings (ibid). It provides evidence on the degree to which any significance results depend on this untestable assumption.

3. Data and descriptive statistics

The data for this study were sourced from a farm level survey conducted in 2011 in 30 cassava growing communities from Atwima Nwabiagya District of Ashanti Region, Techiman municipality of Brong Ahafo Region and Fanteakwa District of Eastern Region, in Ghana. The districts were selected from the Root and tuber improvement and marketing programmes' operational districts to reflect high cassava production and marketing of cassava in each region. Ten communities were randomly selected from the list of communities of each district and fifteen cassava producers in each community were interviewed. A total of four hundred and fifty (450) cassava farmers were sampled for the study. Information was gathered through face to face interviews using structured and semi structured questionnaires.

The dependent variable used in this study is a dummy variable indicating adoption and non adoption of improved cassava variety. Adopters were classified as farmers who planted any of the improved cassava varieties irrespective of the area planted, and non-adopters were those who did not cultivate any of the improved varieties in 2009-2011 production season. The binary treatment indicator is A = 1 for adopters and A = 0 for non-adopters. An outcome variable used to measure welfare[1] was crop income[2] . A Crop income[3] includes income from food crops such as cassava, maize, yam, plantain, rice, cocoyam and vegetables. We included the following household characteristics that influence adoption and welfare a prior: farm and farmer characteristics e.g. household size total farm size, institutional and access related variables e.g. extension contact, credit access and technology specific characteristics e.g. yield, labour

[1] Though there are different measures and different concepts of farmers' wellbeing (monetary and non-monetary indicators etc.), due to data availability farmers' welfare is measured through crop income

[2] Total crop income was used since nonfarm activities were not significant

[3] The survey used does not provide information on inputs use, either physical or human inputs (such as labour, in terms of man-hours per land). However, since the survey was cross-sectional and was undertaken in 1-year time, it is assumed that all farmers face the same prices of inputs.

requirement. Welfare effect of adoption on men and women are compared. Women are assumed to rely so much on food crops such as cassava and cocoyam and men on cash crops such as cocoa and coffee for their livelihoods in Ghana (Doss, 2002). We therefore hypothesize positive effect of adoption of improved cassava varieties on women farmers' incomes and food security.

Summary statistics and statistical significance tests on equality of means for continuous variables and equality of proportions for binary variables for both women and men adopters and non adopters are presented in Tables 1 and 2. The observed mean difference of 0.11 in the effects of treatment for men (0.29) and women (0.18) is statistically significant at 1% level indicating the presence of gender heterogeneous treatment effects. The difference in adoption rates between men and women reflects the fact that men in the area are more informed about an agricultural technology than women. Doss (2001) finds that men-headed farmers adopt new agricultural technologies faster than women farmers due to access to complementary inputs such as, access to credit and access to extension services. Women often lack capacity (mobility and funds), education, self-confidence, and more limited opportunities to join in groups and organizations due to cultural differences, which often serve as platforms and avenues for consultations and information-sharing with other actors including policymakers, researchers, and technical experts (Ragasa, 2012). There are also significant differences in the means of variables between adopters and non adopters of both men and women participants. There are therefore some differences between participants and non-participants with respect to farm and farmer characteristics and technology specific characteristics. As regards the outcome variables there are significant differences between women adopters and non adopters concerning crop income. Women adopters have more incomes than non adopters and the difference is statistically significant. Women adopters and non adopters differ significantly in terms of education, awareness and technology specific variables. Women adopters have more years of education than their non adopter counterparts. On average, a higher proportion of women adopters are aware of improved cassava varieties. There are also significant differences between women adopters and non-adopters with respect to perceptions about the existing improved cassava varieties.

There are statistically significant mean differences between men adopters and non adopters of total cropped area, extension visits, participation in demonstrations, perceptions of characteristics of improved varieties about disease resistance, labour requirement and yield d between men adopters and non-adopters. Men adopters have larger crop land (mean 14 acres) than non adopters (mean 10 acres) and the difference is significant at 1% level. This suggests land size may be correlated with adoption of improved cassava varieties. Men adopters and non adopters also vary significantly in terms of extension visits and participation in field demonstrations. Men adopters seem to have more visits and have attended more demonstrations than non adopters. This also lends support to the importance of institutional factors in adoption of improved technologies. There are also significant differences between adopters and non-adopters with respect to perceptions about the existing improved cassava varieties. The mean differences amongst the perception indicators are all statistically significant at 1% between men adopters and non adopters.

The discussions above have shown the differences between men and women adopters and non adopters and have centered on mean differences in the outcome variable and farm and farmer characteristics and other characteristics of the improved cassava varieties. The discussions above especially concerning the outcome variables suggest that improved technology may have a role in improving household welfare, but because adoption is endogenous, a simple comparison of the welfare indicators of adopters and non- adopters has no causal interpretation. That is, the above differences may not be the result of improved cassava varieties adoption but instead may be due to other factors, such as differences in household characteristics and farm characteristics as mentioned above. The outcome effect on individuals who adopt improved cassava varieties might have been achieved even without adoption i.e. the counterfactual effect. There is therefore the need to further investigate these outcome effects by applying other rigorous analysis to test the impact of improved cassava varieties adoption on farmers' welfare. In consequence, we apply propensity score matching methods that control for these observable characteristics to isolate the intrinsic impact of improved cassava adoption on farm household's welfare.

4. Empirical results

The logit regression model was used to estimate propensity score matching for participant (adopters) and non-participants (non adopters) farmers. Results of propensity scores for whole sample and subsamples (men and women) are presented in Table 3.The low pseudo-R^2 of 0.17, 0.16 and 0.23 for whole sample, women and men respectively shows that farmers growing cassava do not have many distinct characteristics overall and as such finding a good match between adopters and non-adopters becomes easier.

Looking into the estimated coefficients, the results indicate that participation in improved cassava varieties is significantly influenced by seven explanatory variables. Total cropped area, hired labour, number of times of extension visits, awareness, credit access, distance to input and output market and perception that improved varieties are is less susceptible to diseases and pest than local are significant variables which affect the farmers decision to participate in the improved cassava varieties. The likelihood of adoption of improved varieties is greatly influenced by total cropped area i.e. farm size. Farmers with larger farm sizes are more likely to try new and improved varieties on a part of their field. This result is consistent with Morris *et al*. (1999) study on maize impact in Ghana that found positive correlation of land size on improved maize participation. Dankyi and Adjekum (2007) also found positive correlation between land size and adoption of improved cassava varieties in southern Ghana. The ability to hire labour has the propensity to increase participation in improved cassava varieties. The results show that women in particular have high propensity to participate in improved cassava varieties if they were able to hire labour as depicted by the high positive and significant coefficient on hired labour. Women also have a high propensity to participate in improved cassava varieties if they had access to credit. The coefficient is positive and significant at 5%. This result is consistent with many studies that found that lack of access to credit by women farmers restricts women's participation in improved technologies (Ani *et al*. , 2004; Doss and Morris, 2001; Shiferaw *et al*., 2008). Numbers of times of extension visits and Knowledge or awareness of improved technologies are proxies for access to information. These two variables are positive and significant at 5% and 1% respectively. Agricultural extension is the system of learning and building human capital of farmers through the provision of information and demonstrations, exposing farmers to technologies which can increase agricultural productivity and, in turn, income and welfare. Farmers have high propensity to participate in improved cassava varieties if they were frequently visited by extension agents. The propensity to participate also correlates with knowledge of improved varieties. This positive effect of farmer technology awareness variable is consistent with Kaliba *et al*. (2000) for maize varieties, Kristjanson *et al*. (2005) for cowpea varieties, Shiferaw *et al*. (2008) for improved pigeon pea varieties in Tanzania and Gebreselassie and Sanders (2008) for sorghum in Ethiopia. Table 4 shows the distribution of the propensity scores. The estimated propensity scores vary between 0.02 and 0.96 (mean =0.42) for adopters and between 0.004 and 0.83 (mean = 0.0.19) non adopters. The common support region would then lie between 0.02 and 0.83. In other words, cassava farmers whose estimated propensity scores are less than 0.02 and larger than 0.83 are not considered for the matching exercise. As a result of this restriction, 44 adopters were discarded from the analysis.

The common support condition was imposed and the balancing property was satisfied in all the estimated regression models. The distribution of the propensity scores and the region of common support before and after matching are shown in Fig. 1. The density distributions of the propensity scores for adopters and non-adopters also support the result above where there are good overlaps. The bottom half of each graph shows the propensity score distribution for the non-treated, while the upper-half refers to the treated individuals. The y-axis indicates the frequency of the propensity score distribution.

The indicators of matching quality are provided in Table 5 whilst the results of treatment effects (ATE, ATT and ATU) for both men and women farmers, all estimated by the nearest neighbour matching method are presented in Table 6. The standardized bias difference between treatment and control samples are used as a convenient way to quantify the bias between treatment and control samples. In all the cases, it is obvious that sample differences in the raw data (unmatched data) significantly exceed those in the samples of matched cases. The low pseudo-R^2 and the insignificant likelihood ratio tests support the hypothesis that both groups have the same distribution in covariates X after matching. In addition the indicators of matching quality show substantial reduction in absolute bias for all the outcome variables. As indicated in Table 5 the mean bias in the covariates X after matching lies below the 20% level of bias reduction suggested by Rosenbaum and Rubin (1985).These results clearly show that the matching procedure is able to balance the characteristics in the treated and the matched comparison groups. Therefore the results are used to evaluate the effect of adoption of improved cassava technology among groups of farmers having similar observed characteristics. This allowed us to compare observed outcomes for adopters with those of a comparison group sharing a common support.

The results of the treatment effects (ATE, ATT and ATU) for whole sample, men and women farmers indicate that improved cassava adoption positively and significantly increases total crop income. Focusing on the ATT the results show that participation in improved cassava varieties has positive and significant impact on farmers total crop incomes. The improved cassava adoption impact on whole sample results in total income increases of ₵1502 (USD 863) per hectare. Comparing the adoption effect on men and women farmers, the results revealed that women benefited more from participation in improved cassava than men. The increase in total crop incomes for women is ₵3173 (USD 1823) whilst that of men is ₵149 (USD 86) per hectare. The increase in total crop incomes for women is significant at 1%. The finding here lends support to many studies (Mendola, 2007; Kassie *et al*., 2010; Asfaw *et al*., 2012) that have found positive impact of improved varieties adoption on farmers' incomes. For women the results indicate their reliance on food crop production for their livelihoods. Doss (2001) in her study of gender patterns of cropping in Ghana though did not find any particular crop belonging to any particular gender but concluded that women particularly concentrate on food crops production. This study affirms that finding.

The sensitivity analysis showing the null hypothesis of no effect of improved cassava technology adoption was carried out using Rosenbaum bounds sensitivity analysis obtained using the rbounds command in Stata 11.2 and are shown in Table 7. As noted by Hujer *et al.* (2004), sensitivity analyses for insignificant ATT estimates is not meaningful and thus are omitted. For the statistically significant effects, the value of *gamma* (Γ) must be increased until the inference about the treatment effect changed. The $p-$ critical values represent the upper bound of the p value from the Wilcoxon signed rank test for estimated adoption effect (ATT) for each level of unobserved selection bias (Γ). Given that the estimated treatment effect is positive, the lower bounds under the assumption that the true treatment effect has been underestimated were less interesting (Becker and Caliendo, 2007) and therefore not reported.

Table 7 shows that the null hypothesis of no effect of improved cassava technology adoption on outcome variables is not plausible. The positive effect of adoption is not sensitive to selection bias due to unobserved variables, even if we allow adopters and non-adopters to differ by as much as 100% (Γ =2) in terms of unobserved covariate. The critical value of Γ, at which point we would have to question our conclusion of a positive effect of improved cassava technology adoption, starts from $\Gamma = 2.5$. This is a large value since the most important variables that affect both the adoption decision and the outcome variable are included. Besides, the sensitivity results are worst case scenarios (Becker and Caliendo, 2007). That is, a critical value of $\Gamma = 2.5$ does not mean that unobserved heterogeneity exists and adoption of improved cassava technology has no effect on the crop income. It only states that the confidence interval for the effect would include zero if an unobserved variable caused the odds ratio of adoption to differ between adopters and non adopters groups by a factor of 2.5. Based on this result, it is concluded that the ATT estimates in Table 6 are pure effect of improved cassava technology adoption.

5. Conclusion and policy implication

The impact of improved cassava adoption on farmers' welfare was investigated to stimulate policy makers' commitment to cassava technology generation and dissemination. The study used the non-parametric propensity score matching analyses in pursuance of whether adopting improved technologies causes resource-poor farmers to improve their incomes and thereby improve livelihoods. The matching method made comparison between those who have adopted and those who have not adopted and drawn conclusions based only on those who have adopted improved cassava varieties. In addition, the Rosenbaum bounds procedure was used to check the sensitivity of the estimated adoption effect to unobserved selection bias. The results revealed that adoption of improved cassava varieties was associated with increased crop income. The impact is more realized in women farmers than men farmers. The results are insensitive to unobserved selection bias. The implication is that of the many factors that might impact income of cassava farmers in the study area the potential direct role of improved cassava varieties cannot be underestimated.

The impact assessment has demonstrated the need to focus more attention to the adoption of improved cassava varieties. The fact that women farmers benefit more from improved cassava production is enough to pay more attention to improved cassava production and dissemination in the country. The analysis of the determinants of adoption generated very interesting results. Awareness and participation in farmer field days/ demonstrations are important prerequisite for improved cassava adoption. This implies the need for policy to strengthen and leverage research institutions and extension services to promote and create awareness about the existing improved cassava varieties. The government should play a leading role in technology promotion and dissemination. Awareness creation for improved varieties, in addition to increased availability of improved cassava varieties can accelerate and expand adoption.

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Table 1. Descriptive statistics of women participation of improved cassava varieties

Variables	Adopters N=33(18.75)		Non adopters N=143(81.25%)		Diff. in means
	Mean	s.d	Mean	s.d	
Treatment variable					
1 if farmer grows improved cassava variety, 0 otherwise					
Outcome variable					
Total income from crops(₵/ha)	4093.66	5094.13	1642.78	1657.25	2450.88***
Farm characteristics					
Age of farm household head (years)	46.48	11.11	49.46	12.64	2.97
Number of years in formal education	6.93	4.23	5.35	4.84	1.58**
Number of years in farming(years)	22.00	12.74	22.87	14.04	0.87
Total cropped area (ha)	2.53	1.55	3.04	2.70	0.50
Hiring of labour for cassava production (1=yes)	0.90	0.29	0.85	0.35	0.05
Institutional and access related variables					
Extension contact (1=yes)	0.54	0.50	0.60	0.48	0.06
Number of Times of extension agents visit	2.63	8.24	1.97	2.79	0.66
Participation in cassava field day/demonstration (1=yes)	0.15	0.36	0.08	0.2	0.07
If farm household head knows about an improved cassava variety(1=yes)	1.00	0.00	0.92	0.26	0.08*
Credit access(1=yes)	0.09	0.29	0.14	0.35	0.05
Own land for farming (1=yes)	0.60	0.49	0.68	0.26	0.08
Distance to output and input market (km)	5.11	3.7	6.95	7.00	1.84
Technology characteristics					
If farm household head perceives that improved cassava is less susceptible to diseases and pest than local(1=yes)	0.21	0.41	0.08	0.27	0.12**
If farm household head perceives that improved cassava requires more labour than local(1=yes)	0.05	0.29	0.04	0.21	0.04
If farm household head perceives that improved cassava yields more than local(1=yes)	0.21	0.41	0.08	0.27	0.12**

Source; Farm level survey, 2011

***significant at 1%, **significant at 5%, * significant at 10%

Table 2. Descriptive statistics of men participation in improved cassava varieties

Variables	Adopters N=82(29.92%)		Non adopters N=192 (70.08%)		Diff. in means
	Mean	s.d	Mean	s.d	
Treatment variable					
1 if farmer grows improved cassava variety, 0 otherwise					
Outcome variable					
Total income from crops(₵)	2277.47	3264.98	1846.17	1992.12	431.30
Farm and farmer characteristics					
Age of farm household head (years)	44.56	11.20	44.63	12.53	0.06
Number of years in formal education	8.93	4.08	8.30	4.40	0.63
Number of years in farming(years)	18.04	10.51	18.23	11.67	0.22
Total cropped area (ha)	5.60	5.04	3.86	3.50	1.84***
Hiring of labour for cassava production (1=yes)	0.87	0.32	0.84	0.35	0.02
Institutional and access related variables					
Extension contact (1=yes)	0.63	0.48	0.54	0.49	0.09
Number of Times of extension agents visit	3.74	7.92	1.81	3.06	1.93***
Participation in cassava field day/demonstration (1=yes)	0.17	0.37	0.09	0.29	0.07*
If farm household head knows about an improved cassava variety(1=yes)	0.96	0.18	0.94	0.23	0.02
Credit access(1=yes)	0.15	0.36	0.07	0.26	0.08
Own land for farming (1=yes)	0.51	0.50	0.55	0.49	0.04
Distance to output and input market (km)	7.45	4.10	7.44	6.40	1.84
Technology characteristics					
If farm household head perceives that improved cassava is less susceptible to diseases and pest than local(1=yes)	0.39	0.49	0.07	0.25	0.32***
If farm household head perceives that improved cassava requires more labour than local(1=yes)	0.31	0.46	0.05	0.22	0.26***
If farm household head perceives that improved cassava yields more than local(1=yes)	0.45	0.26	0.08	0.27	0.37***

Source; Farm level survey, 2011

***significant at 1%, **significant at 5%, * significant at 10%

Table 3. Logit estimates of propensity scores for whole sample and subsample (men and women)

Variables	Whole sample (N=450)		Men (N=274)		Women(176)	
	Coeff.	Std error	Coeff.	Std error	Coeff.	Std error
Farm and farm characteristics						
Age of farm household head (years)	-0.008	0.103	-0.038	0.023	0.011	0.018
Number of family members	0.012	0.008	-0.025	0.364	-0.046	0.065
Gender of farm household head (1=Women)	-0.208	0.281	-	-	-	-
Number of years in formal education	0.022	0.029	0.064	0.53	0.001	0.395
Number of years in farming(years)	0.002	0.012	0.025	0.020	-0.010	0.018
Total cropped area (ha)	0.037***	0.013	-0.055**	0.045	0.050***	0.017
Hiring of labour for cassava production (1=yes)	0.919***	0.417	0.868	0.782	1.199**	0.554
Institutional and access related variables						
Extension contact (1=yes)	-0.392	0.287	-0.681	0.499	-0.265	0.373
Number of Times of extension agents visit	0.057**	0.02	0.032	0.043	0.068**	0.037
Participation in cassava field day/demonstration (1=yes)	0.625	0.391	0.889	0.782	0.474	0510
If farm household head knows about an improved cassava variety(1=yes)	2.150***	0.755	0.789	0.599	1.219	0.84
Credit access(1=yes)	0.326	0.394	-0.119**	0.060	0.915**	0.512
Own land for farming (1=yes)	-0.325	0.258	-0.507	0.300	-0.260	0.330
Distance to output and input market	-0.040**	0.025	0.119**	0.060	-0.045	0.028
Technology characteristics						
If farm household head perceives that improved cassava is less susceptible to diseases and pest than local(1=yes)	1.056**	0.590	1.706	1.257	1.012	0.724
If farm household head perceives that improved cassava requires more labour than local(1=yes)	0.550	0.530	-0.789	1.151	0.741	0.691
If farm household head perceives that improved cassava yields more than local(1=yes)	0.971	0.628	0.782	1.235	1.216	0.814
Constant	-3.95***	1.04	0.450	1.452	4.001***	1.243
Pseudo R^2	0.17		0.16		0.23	
P-value	0.000		0.031		0.000	
N	450		176		274	
Log likelihood	-209.763		-69.219		-128.683	

Source; Farm level survey, 2011

*significant at 10% level, **significant at 5% level, *** significant at 1% level

Table 4. Estimated distributions of propensity scores

Group	Observation	Mean	STD	Minimum	Maximum
Total household	450	0.255	0.202	0.004	0.957
Adopters	115	0.419	0.259	0.020	0.957
Non adopters	335	0.199	0.140	0.004	0.830

Table 5. PSM quality indicators before and after matching

	Outcome indicator	Calliper	Pseudo R^2 (Unmatched)	Pseudo R^2 (matched)	P-value[4] (unmatched)	P-value (matched)	Mean absolute bias (unmatched)[5]	Mean absolute bias (matched)[6]	Absolute bias reduction[7]
All farmers	Crop income (₵)	0.005	0.178	0.034	0.000	0.944	26.3	7.9	70.00
Women	Crop income (₵)	0.005	0.164	0.190	0.028	0.608	23.9	17.5	27.00
Men	Crop income (₵)	0.005	0.231	0.122	0.000	0.481	27.6	13.8	50.00

Source; Farm level survey, 2011

Note: Pseudo-R^2 from logit estimation indicates the goodness of fit or how well the regressors explain the probability to grow improved cassava variety. 1USD= ₵1.74 in 2011

[4] P-Value of likelihood ratio test ($Pr > \chi^2$)

[5] $MAB_{um} = 100 * (\overline{X_1}) - (\overline{X_0}) \left(\frac{1}{2} (A_1(X) + A_0(X) \right)^{\frac{1}{2}}$

[6] $MAB_{m} = 100 * (\overline{X_1}) - (\overline{X_0}) \left(\frac{1}{2} (A_{1m}(X) + A_{0m}(X) \right)^{\frac{1}{2}}$

[7] $BR_T = 100 \left(1 - \frac{MAB_m}{MAB_{um}} \right)$

Table 6. Treatment effects and results of sensitivity analysis, whole sample, Women and men

	Outcome indicator	Calliper	PSM			Treated		Control	
			ATE	ATU	ATT	On support	Off support	On support	Off support
All farmers	Crop income (₵)	0.005	1558.21*** (2.62)	1613.67** (2.28)	1502.74*** (2.99)	71	44	71	264
Women	Crop income (₵)	0.5	3327.48*** (2.78)	3489.33*** (2.75)	3173.00*** (2.75)	22	11	21	111
Men	Crop income (₵)	0.5	98.866 (0.18)	46.75 (0.08)	148.5 (0.26)	42	40	40	152

Source; Farm level survey, 2011

Notes: t-statistics are in parentheses.
* Denotes significant at 10%.
** Denotes significant at 5%.
*** Denotes significant at 1%.
1USD=₵1.74 in 2011

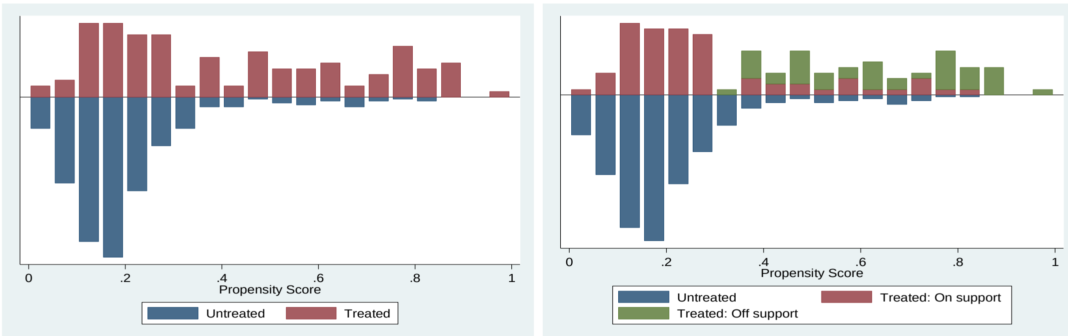
Table 7. Rosenbaum Bound Sensitivity Analysis Test for Hidden Bias

Outcomes	[8] Γ =1	Γ =1.5	Γ =2	Γ =2.5	Γ =3	Γ =3.5	Γ =4
Whole sample							
Crop income	0.077	0.016	0.050	0.786	0.923	0.976	0.993
Women							
Crop income	0.011	0.067	0.016	0.279	0.392	0.496	0.586
Men							
Crop income	0.046	0.085	0.097	0.995	0.999	0.999	0.999

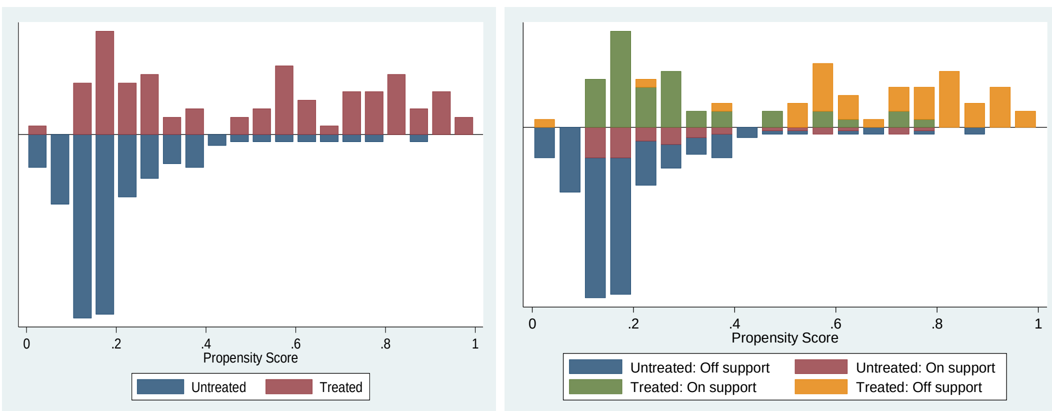
Source; Farm level survey, 2011

[8] Γ =log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated

All households' participation in cassava varieties



Males' participation in cassava varieties before and after



Females' participation in cassava varieties before and after

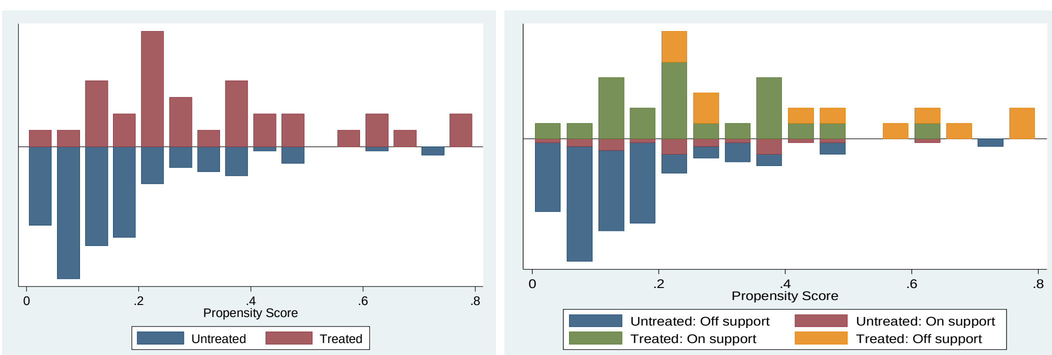


Figure1. Propensity score distribution and common support for propensity score estimation for matched and unmatched samples. Source: Own calculation