Impact of cocoa agroforests on yield and household income: Evidence from Ghana

Victor Owusu* and **Frederick Kwabena Frimpong**
Department of Agricultural Economics, Agribusiness and Extension,
Kwame Nkrumah, University Science and Technology, Kumasi, Ghana

Contributed Paper prepared for presentation at the 88th Annual Conference of the Agricultural Economics Society, AgroParisTech, Paris, France

9 - 11 April 2014

***Corresponding Author:**
Victor Owusu
Department of Agricultural Economics, Agribusiness and Extension
Kwame Nkrumah University of Science and Technology
Kumasi, Ghana
Tel; 233 242 832330
Email: vowusu.agric@knust.edu.gh

Abstract

Using a cross-sectional data collected on 400 cocoa farmers from the Ashanti and Western Regions of Ghana, this paper provides empirical evidence on the impacts of cocoa agroforests on yield and household income. The propensity-score matching model was employed. The heterogeneity of high, medium and low shade adopters is statistically addressed. The empirical results generally indicate that adoption of cocoa agroforests has significant positive impacts on yield and household income. The impact on yields for low shade adopters was higher than medium shade and high shade adopters of cocoa agroforests. The paper provides useful policy recommendations based on the empirical magnitudes and directions on sustainable cocoa production and household welfare.

Keywords: Adoption, Cocoa agroforests, Ghana, Household income, Impact, Yield

JEL code: Q1, Q23

1. Introduction

Cocoa is an economic crop cultivated in the humid tropics of West Africa, South-East Asia, South-America and the Caribbean. It is estimated that about 5–6 million smallholder farmers earn most or all of their cash income from cocoa production (Clay, 2004). In Ghana, the cocoa sub-sector accounts for over 20.5 percent of its export earnings, 3.3 percent of GDP and employs 24 percent of the labor force (FASDEP, 2002). It serves as a major source of livelihoods to smallholder farmers and accounts for 55 percent of the total household income (IITA, 2002; Asamoah and Baah, 2003).

The cocoa sub-sector in Ghana has benefited immensely from the implementation of several policies over the years in an effort to increase production. These include the Development Strategy for Cocoa, Cocoa Disease and Pest Control (CODAPEC) programme and the Cocoa Hi-TECH programme (Dormon *et al*., 2004; Bosompem *et al*. 2010). Although these laudable policy instruments have achieved some significant success (COCOBOD, 2011), the average yield per hectare is about 450 kg (MMYE, 2008), which is far below that of Malaysia and Indonesia where average yield exceeds 1000 kg/hectare. Evidence suggests that the growth in the cocoa sub-sector in Ghana has been achieved through increased acreages rather than improved yield (MOFA, 2006; COCOBOD, 2007). The increasingly low cocoa yields in Ghana is such that average income per capita for a cocoa farm household is as low as GH¢1 per day (Hainmueller *et al*., 2011). According to Dormon *et al.* (2004), the relatively low productivity of cocoa in Ghana could be attributed to a number of reasons, including poor farm maintenance practices, planting low-yielding varieties, the incidence of pest and diseases, decline in soil fertility, inconsistency in rainfall pattern and non-adoption of improved technologies.

The adoption of environmentally sound and sustainable cocoa production through cocoa agroforest has been suggested as a useful technology to improve cocoa yields in Ghana, and other cocoa producing countries where marginal lands are increasingly being brought under cultivation (Asare, 2005; Boateng, 2008). Cocoa agroforest is the intercropping of cocoa trees with fruit, commercial timber, or fast-growing and high-value tree species (Duguma *et al*., 2001). Apart from the additional income to farmers, cocoa agroforest provides food, minimizes risk through diversification and provides shade for cocoa plants (Duguma *et al*., 2001, Isaac *et al* 2007). Cocoa agroforests also mitigate deforestation through tree planting, and combat land depletion because of its potential for soil conservation. In Ghana, the existing cocoa agroforests are the high shade cocoa farms with about 22 – 30 forest trees/ha (STCP, 2002; Ofori-Frimpong et al., 2007), the medium shade cocoa farms with 15 – 18 forest trees/ha (STCP, 2002; CRIG, 2010) and the low shade cocoa farms with 5-6 trees/ha (Ruf, 2011; UNDP, 2011). In addition, Uribe *et al* (2001) reports of the full-sun cocoa agroforests where cocoa farms have no shade trees in them.

A number of studies have considered the relevance of cocoa yields in general (Clay, 2004; Dormon *et al*. 2004; Hainmueller *et al*., 2011; Wiredu *et al*. 2011), and the adoption of cocoa agroforests in Africa (Uribe *et al*., 2001; Ruf, 2011; UNDP, 2011) and in Ghana (STCP, 2002; Ofori-Frimpong *et al*., 2007). These studies have tended not to consider the direct impact of cocoa agroforests on cocoa yields. Asare (2005) and Steffan-Dewenter *et al*. (2007) for instance, pointed out that the trade-off between cocoa productivity and various shade levels in Ghana has not received much attention. Indeed, rigorous empirical evidence on the impact of cocoa agroforests on yields has been very scanty. The contribution of the present paper therefore is to build on the existing literature by rigorously investigating the impact of adoption of cocoa agroforests on cocoa yield and household income. Two important research questions which arise regarding Ghana and which are addressed in this paper are the following: (1) What are the direct impacts of cocoa agroforests on yield and household income? (2) To what extent do the existing shade regimes under cocoa agroforests in Ghana impact on cocoa yield and household income? The primary objective of the current paper is to examine the impact of cocoa agroforest on the yields and household incomes of cocoa farmers in Ghana. We employed the propensity score matching analysis to account for selection bias that normally arises when unobservable factors influence adoption of the cocoa agroforests and impact outcomes. In addition, the heterogeneity of low, medium and high shade adopters is statistically addressed in the paper.

The remainder of the paper is structured as follows. Section 2 presents a simple model of adoption of cocoa agroforests as well as a description of the propensity score matching approach. Section 3 discusses the data employed in the study. Section 4 discusses the empirical results. Section 5 provides conclusions and policy implications.

2. Conceptual framework

Following the literature on adoption decisions of agricultural households, it is assumed that the cocoa agroforest adoption is a dichotomous choice, where the technology is adopted, if the net benefits from adoption are greater than that from non-adoption. The difference between the net benefits from adoption and non-adoption may be denoted as D^*, such that $D^* > 0$, implying the net benefits from adoption of cocoa agroforest exceeds that of non-adoption. Although D^* is not observable, it can be expressed as a function of observable elements in the following latent variable model:

$$D_i^* = \alpha Z_i + \mu_i, \quad D_i = 1\ [D^* > 0] \tag{1}$$

where D_i is a binary variable that equals 1 if the household i adopts the cocoa agroforest and 0 otherwise, α is a vector of parameters to be estimated, Z_i is a vector of household and plot level characteristics and μ_i is an error term assumed to be normally distributed. The probability of adoption of cocoa agroforest can be represented as:

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\mu_i > -\alpha Z_i) = 1 - F(-\alpha Z_i) \tag{2}$$

where F is a cumulative distribution function and the functional form of F is assumed to follow a logistic distribution.

To link the adoption of cocoa agroforest to cocoa yield or household income, consider a linear specification of the level of cocoa yield or household income Y_i as a function of a vector of explanatory variables X and a dummy variable D that captures the adoption status of the cocoa agroforest. The relationship between cocoa yield or household income and adoption may then be expressed as:

$$Y_i = \beta_1 X_i + \beta_2 D_i + \xi_i \tag{3}$$

where Y_i is cocoa yield or household income of the sampled cocoa farmer i, ξ_i is a normal random disturbance term and D_i is a dummy variable indicating $D_i = 1$ if the farm household adopts the cocoa agroforest and $D_i = 0$, otherwise. The vector X_i summarizes individual and household characteristics as well as farm-level and agroforest-specific characteristics.

From the treatment equation (1) and the outcome equation (3), the relationship between adoption of the cocoa agroforest and cocoa yield or household income may be interdependent, resulting in selection bias. The implication of this is that treatment assignment is not random, with the group of adopters being systematically different. Selection bias normally occurs if unobservable factors influence both error terms in the adoption specification (μ_i) and the yield or household income equation (ξ_i), resulting in correlation of the error terms in the two specifications. The error terms of the treatment and the outcome variables then become correlated such that $corr(\mu, \xi) = \rho$. When $\rho \neq 0$, any standard regression technique such as OLS applied to the regression models produces biased results. The problem of self-selection can be overcome by employing statistical matching approach, which involves the pairing of adopters and non-adopters with similar observable characteristics (Dehejia and Wahba, 2002).

To examine the direct causal effect of adoption of cocoa agroforest on yield or household income, the propensity score matching approach is employed. As indicated previously, the advantages of using the propensity score matching model is to control for self-selection bias that arises when adoption of cocoa agroforest is not randomly assigned. Moreover by using propensity score matching, we assume that both adopters and non-adopters of cocoa agroforest have similar characteristics. Therefore we are able to avoid the possible reverse causality between adoption of cocoa agroforest and cocoa yield or household income.

Rosenbaum and Rubin (1983) define the propensity score $p(Z)$ as the conditional probability of adopting the cocoa agroforest, given pre-adoption characteristics. Thus:

$$p(Z) \equiv Pr\{D=1 \mid Z\} = E\{D \mid Z\} \tag{4}$$

where $D = \{0,1\}$ is the indicator of adoption of the cocoa agroforest and Z is the vector of pre-adoption characteristics. The estimated propensity scores are used to estimate the Average Treatment Effect on the Treated (ATT), which is the parameter of interest as

$$\delta \equiv E\{Y_i^1 - Y_i^0 \mid D_i = 1\} = E\{E\{Y_i^1 \mid D_i = 1, p(Z_i)\} - E\{Y_i^0 \mid D_i = 0, p(Z_i)\} \mid D_i = 1\} \tag{5}$$

where $p(Z_i)$ is the p-score, Y_i^1 and Y_i^0 are the potential outcomes in the two counterfactual situations of receiving treatment and no treatment.

The two important properties of the propensity score matching are the balancing property and the Conditional Independence Assumption (CIA). Testing for the balancing property ascertains if household behavior within each group is actually similar. For efficient and unbiased estimates, the Conditional Independence Assumption (CIA) shouldn't be violated. The Conditional Independence Assumption (CIA) propounds that once the set of observable characteristics, Z are controlled for, the adoption of cocoa agroforest is random and uncorrelated with cocoa yield or household income of the farmer. A further requirement is the common support condition which requires that individuals with the same covariates Z have positive probabilities of being both adopters and non-adopters (Heckman *et al.*, 1999). This indicates that all individuals in the common support region can actually exist in all states ($0 < P(D=1 \mid Z) < 1$).

A comparison of the pseudo-R^2 before and after matching could also be employed to test if there are still some systematic differences in the distribution of the covariates between both groups (Sianesi, 2004). In addition, sensitivity analysis can be undertaken to check if the influence of an unmeasured variable on the selection process is so strong to undermine the matching procedure. Given that it is impossible to estimate the magnitude of the selection bias with non-experimental data, we employ the bounding approach suggested by Rosenbaum (2002).

3. Data collection and description

The data for the study comes from a sample of 400 cocoa farmers in two cocoa growing districts in the Ashanti and the Western Regions of Ghana (see Figure 1). The vegetation is typically, moist semi-deciduous forest with the Forest Ochrosol as the predominant soil type.

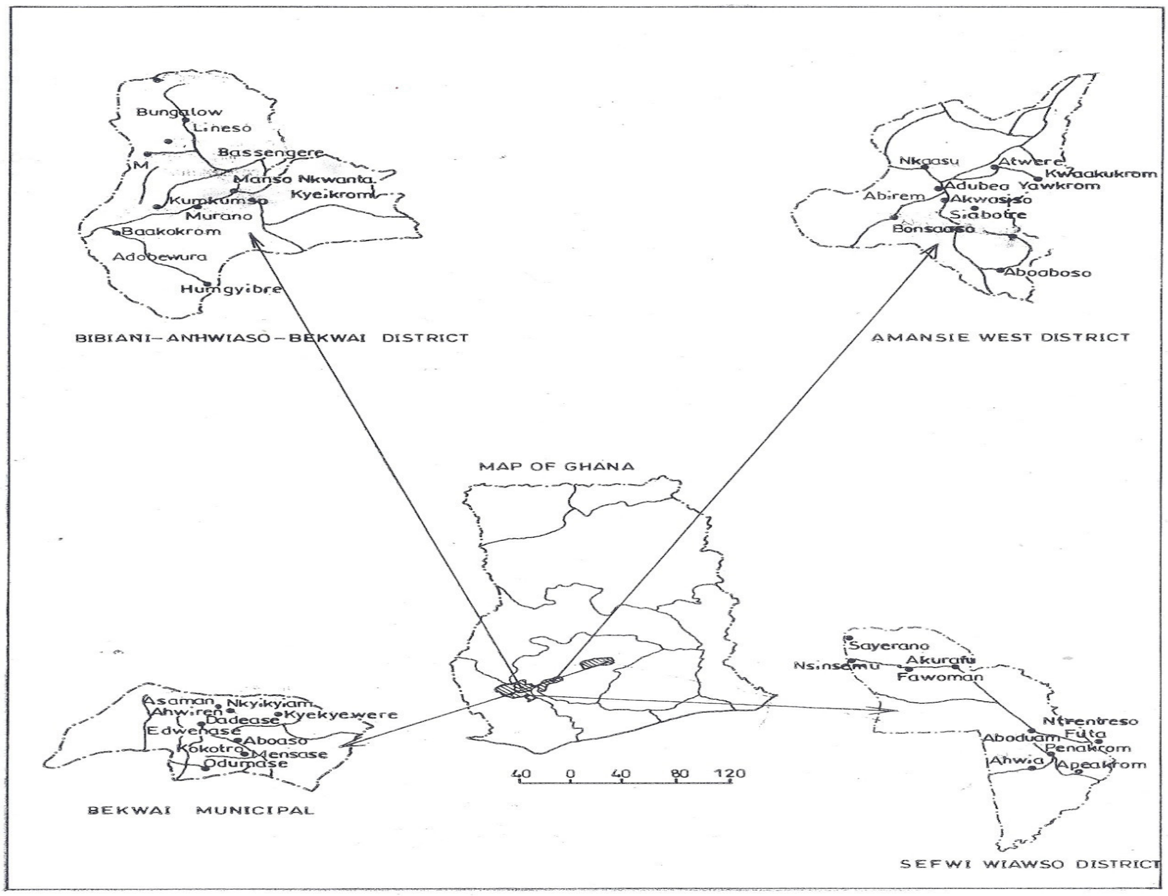

Figure 1. Map of the study area
Source: Department of Geography and Rural Development, KNUST, Kumasi

The rainfall pattern ranges between 1500 mm – 1800 mm with mean monthly temperature between 27^0C – 33^0C. Agriculture is the predominant economic activity with about 70 – 90 percent of the economically active population employed in that sector. Apart from cocoa, farmers in the regions grow food crops such as are maize, yam, cocoyam, plantain cassava, rice, and other tree crops such as coffee and oil palm, and fruit crops such as citrus and avocado.

Multi-stage sampling technique was adopted for the study. In the first stage, 2 cocoa districts each were purposely selected from the two regions. The selected districts were Bibiani/Anhwiaso/Bekwai and Sefwi Wiawso in the Western Region and the Amansie West and Bekwai Municipal in the Ashanti Region. In the second stage, 5 cocoa growing zones were randomly selected from each of the 4 districts. In the third stage, a random sampling of 2 communities from each of the 5 selected cocoa zones. In the final stage, 10 farm households were randomly selected from each of the 2 communities making a total sample of 400 farm households.

Person-to-person interview was employed in the administration of the structured questionnaires during the survey to obtain the relevant information. The data comprised of information on personal and household characteristics of farmers, plot level characteristics, awareness, perceptions of cocoa agroforests, cocoa farm cash - oriented activities, including cocoa yield and household income components.

The descriptive statistics and the differences in means of the variables used in the analyses are presented in Tables 1, 2 and 3 (not presented in the interest of brevity). About 37% of the sampled farmers adopted the low shade technology, 44% adopted the medium shade and 25% adopted the high shade agroforestry technology. Adoption of low shade technology, medium shade technology and high shade technology were all measured as dummy variables, indicating 1 if the farmer adopted these agroforestry technologies and zero otherwise. Total household income was categorized into income from non-farm employment, income from livestock (net sales plus the value of home consumption) and transfers received by the household. It was measured in hundreds of Ghana cedi (GH¢). The average household income for low shade adopters is GH¢33.68 (US$17.70), while the corresponding figure for non-adopters is GH¢28.22 (US$14.83). For medium shade adopters, the average household income is GH¢44.48 (US$23.38), while for non-adopters, it is GH¢31.60 (US$16.61). The average household income for high shade adopters is GH¢33.84 (US$17.79), while for non-adopters, the corresponding figure is GH¢30.89 (US$16.24). The cocoa yield was measured as the output of cocoa beans per hectare (65kg/bag/ha). Of all the shade adoption categories, the mean yield for adopters is higher than non-adopters with the corresponding differences in means, all statistically significant at the 1% level.

There are also significant differences in means of almost all the independent variables investigated in the adoption specification, which clearly indicate that the sampled farmers were statistically different before the matching. Normally, matching should be based on variables that influence both treatment assignment and outcomes and are not affected by the treatment (Caliendo and Kopeinig, 2008). Economic theory informed the choice of the variables employed to predict the propensity scores with the logit models. Notably, sound knowledge of previous research and information about the institutional settings and previous studies on the adoption of agroforests were considered in the specification of the model (Smith and Todd, 2005).

4. Empirical results

The empirical results of the propensity score estimates for low shade, medium shade and high shade adopters are provided in Table 4. The propensity scores which were computed with a logistic model only served as a tool to balance the observed distribution of covariates across the treated and the untreated groups (Lee, 2008; Owusu *et al.* 2011). Therefore, detailed interpretation of the determinants of the adoption of the agroforest is not elaborated in this paper. However it is noteworthy to point out that adoptions of low, medium and high shade agroforests were significantly influenced by farmer-based organization and other relevant indicators controlling for agroforest characteristics. The common support condition was imposed and the balancing property was set and satisfied in all the estimated regression models at 1% level of significance. The distribution of propensity scores for adopters and non-adopters of all the 3 agroforests investigated are shown in Figure 2 (not presented in the interest of brevity). The distribution clearly show that estimating the *p*-score assisted in making the treated and control groups more similar than without the *p*-score, a result which underscores the relevance of the propensity score matching approach.

The results of the treatment effects (ATT) for the adoption of cocoa agroforests computed with the Nearest Neighbor Matching (NNM) algorithm are presented in Table 5. Other matching algorithms were estimated but it was observed that the Nearest Neighbor Matching technique produced consistent and robust estimates of the treatment effects. The matching results generally

Table 4. Logistic estimates of propensity scores of adopters of cocoa agroforests

Variable	Low shade		Medium shade		High shade	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Household characteristics						
AGE	0.6023***	2.74	0.2636	1.46	0.3650**	1.93
AGE2/100	- 0.5093***	-2.49	-0.2979*	1.71	- 0.3326**	-1.92
GENDR	- 3.7050***	-2.61	0.5860	0.54	0.5510	0.54
EDU	0.3413**	2.35	-0.0047	-0.04	0.0235	0.21
MRRD	- 1.2525	-0.97	-3.5649**	-2.12	- 0.1598	-0.21
HHH	3.0432**	2.30	-1.4270	-1.35	1.3163*	1.71
HHS	0.7009***	3.19	-0.2733*	-1.82	0.2378	1.33
CHLD<15	- 0.5493*	-1.73	0.2806	1.40	- 0.0383	-0.20
FRMEXP	- 0.010	-0.08	-0.1616**	-1.93	0.0273	0.38
FBOMEMB	1.9433**	1.98	1.2809*	1.78	0.5540	0.65
Farm characteristics						
LOWN	- 0.1336	-0.29	-0.2415	-0.71	-0.3711**	-2.04
AGECOC	- 0.2683	-1.00	0.1832	1.05	0.1770*	1.64
YRHRV	0.1737	0.90	-0.1419	-0.94	-0.2292**	2.07
PRV_LND_USE	- 0.9325	-1.19	-1.3896**	-2.08	-0.1706	-0.27
SOILTYP	- 1.3021***	-3.21	-0.5242*	-1.71	0.4266*	1.71
Agroforest indicators						
SUSTYLD	0.9599	1.30	-0.2937	0.60	0.2127***	2.89
MULTRVN	-1.5265*	-1.91	0.7026	1.21	0.7010***	2.43
FRTIMP	2.7645***	2.60	0.9736	1.29	0.3013	0.38
ERCNTRL	0.1788	0.19	1.4058*	1.51	-0.6416	-0.91
WDCNTRL	-0.6489	-0.75	1.0975	1.45	0.5132	0.67
BIODIMP	2.1419**	2.37	1.3216*	1.78	1.1637*	1.65
CONSTANT	-5.2043	-1.06	6.6109	1.45	5.7721	1.19
Pseudo – R^2	0.4616		0.4880		0.4233	
LR Chi2 21	67.87 (0.0000)		43.45 (0.0028)		24.77 (0.0000)	
Log likelihood	-39.58		-53.71		-52.498	
No. of Observations	400		400		400	

*Significant at 10%, **Significant at 5%, ***Significant at 1%

Source: Authors computation,

indicate that, adoption of cocoa agroforests shows significant positive impacts on cocoa yield and household income. For the low shade adopters, the causal effect of adoption is 63.96 which is the average difference between incomes of similar pairs of households that belong to different adoption status. The magnitude of the effect suggest that the average treatment effect of adoption of low shade tends to increase household income by GH¢63.96 (US$33.62), The coefficient for yield indicates that on the average, adoption of low shade cocoa agroforest increases cocoa yield of a farm household by 14.48 kg/ha. The reduction in mean absolute standardized bias from 23.0% to 7.15% indicates a substantial reduction in bias as a result of employing the matching technique (Table 6). The magnitude of the effect of 78.93 for medium shade adopters suggests that the average treatment effect of adoption of the medium shade increases household income by GH¢78.93 (US$41.49). The causal effect for yield indicates that adoption of medium

Table 5. Estimates of treatment effects and sensitivity analysis

Sample	Outcome indicators	ATT	Hidden bias Γ	Treated		Control	
				On-support	Off-support	On-support	Off-support
Low Shade	FCY	14.48*** (4.40)	1.15-2.00	139	-	261	-
	HHINC	63.96** (2.67)	1.00-1.95	143	99	158	-
Medium Shade	FCY	12.01** (2.66)	1.00-2.00	245	85	70	-
	HHINC	78.93*** (3.14)	1.05-2.00	315	-	85	-
High Shade	FCY	4.79** (2.60)	1.15-1.70	176	131	93	-
	HHINC	23.34** (2.91)	1.10-2.00	205	175	20	-

Note: *t*-values in parentheses;
* Significant at 10%, ** Significant at 5% and *** Significant at 1%.
Outcome indicators: FCY denotes cocoa yield of the farmer in 65kg/bag, HHINC denotes household income of the farmer in GH¢. Exchange rate: US$1=GH¢1.9023 in 2012
Source: Authors' computations

shade cocoa agroforest increases cocoa yield by 12.01 kg/ha. The mean absolute bias of 64.32% is quite substantial. Similarly, the causal effect of 23.34 for high shade adopters indicates that the average treatment effect of adoption increases the household income by GH¢23.34 (US$12.27). Adopters of high shade cocoa agroforest are more likely to increase their cocoa yield by 14.79 kg/ha (on average). A reduction in mean absolute bias of 17.2% to 5.23% is an indication that by choosing the matching algorithm and propensity score estimation, the covariates are balanced. The average treatment effects on yield from adopting cocoa agroforests indicate that low shade adopters performed better in terms of cocoa yields than high shade and medium shade adopters. This empirical finding is in line with an assertion by Stephan-Dewenter *et al.* (2007) that low shade cocoa agroforest provides the best available compromise between economic forces and ecological need.

Table 6. Indicators of matching quality

Sample	Outcome indicator	Pseudo-R^2 (unmatched)	Pseudo-R^2 (matched)	*p*-value (unmatched)	*p*-value (matched)	Mean absolute bias (unmatched)	Mean absolute bias (matched)	Absolute bias reduction
Low Shade	FCY	0.469	0.031	0.000	0.214	23.0	7.15	68.91
	HHINC	0.381	0.012	0.000	0.331	20.1	11.03	45.12
Medium Shade	FCY	0.484	0.026	0.000	0.119	25.7	9.17	64.32
	HHINC	0.258	0.022	0.003	0.185	19.5	8.70	55.38
High Shade	FCY	0.249	0.011	0.007	0.143	17.2	5.23	69.59
	HHINC	0.236	0.098	0.000	0.171	26.5	10.16	61.66

Source: Authors' computations

The results from the sensitivity analysis on hidden bias, which shows the critical levels of gamma (Γ) at which the causal inference of significant adoption impact may be questioned, are presented in Table 4. The bounding approach suggested by Rosenbaum (2002) was employed. Given that sensitivity analysis for insignificant effects is not meaningful, Rosenbaum bounds were calculated only for treatment effects that are significantly different from zero (Hujer *et al.*, 2004). For example, the value of 1.15-1.70 for high shade adopters implies that if cocoa farmers that have the same Z-vector differ in their odds of adoption by a factor of 15–70%, the significance of the adoption effect on yield may be questionable. The lowest critical value of $\Gamma = 1.00$ and the highest critical value $\Gamma = 2.00$ clearly indicate that even large amounts of unobserved heterogeneity would not alter the inference about the estimated treatment effects, indicating that the results are generally insensitive to hidden bias.

The mean absolute standardized bias before and after matching presented in the last column of Table 5 shows substantial reduction in absolute bias of the outcome variables for low, medium and high shade adopters of cocoa agroforestry technology. The *pseudo*-R^2s after matching are averagely low with none of the diagnostic statistics being significantly different from zero, suggesting that the overall results from the matching procedure are satisfactory in balancing the covariates among the low, medium and high shade adopters of cocoa agroforests (Sianesi, 2004).

5. Conclusions

Using a sample of 400 farm households from the Ashanti and Western Regions of Ghana, the present paper investigated the impacts of adoption of cocoa agroforests on cocoa yield and household income. A propensity score matching model was employed to account for selection bias that normally occurs when unobservable factors influence both adoption in cocoa agroforest and yield or household income. By explicitly referring to the causal relationship between adoption of cocoa agroforest and yield or household income, the paper seeks to address counterfactual questions that may be significant in predicting the impacts of policy changes.

The empirical analysis was conducted specifically for the adoption of low, medium and high shade agroforests. The results generally indicate that adoption of cocoa agroforest assisted farm households to improve their cocoa yields thereby increasing their household incomes. The estimates differentiated by shading regimes show that the gains from adoption of cocoa agroforest are higher for low shade adopters than medium and high shade adopters. In particular, adoption was found to have a positive and significant impact on yields and household incomes for low, medium and high shade adopters of cocoa agroforests. In terms of household income, the gains from adoption tend to be higher for medium shade adopters than high shade and low shade adopters.

The results from the study indicate that the promotion of technology adoption by policy makers and other stakeholders in rural areas of developing countries is an appropriate policy instrument. The implication for introducing cocoa agroforests in developing countries requires that cocoa farmers are trained and educated through extension on sustainable yield practices such as fertility improvement, erosion control, pruning and weed control. This would in effect, promote farm intensification rather than expansion into new forest areas should the Government provide incentive packages to farmers who practice sustainable cocoa farming.

References

Asamoah, M. and Baah, F. Improving Research-Farmer Linkages: The role of CRIG. Conference paper (4th International Seminar on Cocoa-Pests and Diseases (INCOPED), Accra, Ghana, 19th-21st October 2003).

Asare, R. Cocoa Agroforests in West Africa. A Look at Activities on Preferred Trees in the Farming Systems. Forest and Landscape Working Papers no. 6-2005 Denmark, (2005).

Boateng, I. The impact of agroforestry on livelihoods: A case study of selected communities of Offinso, Afigya Sekyere and Atwima Districts. Kwame Nkrumah University of Science and Technology, Department of Agroforestry. (2008) pp. 15-17

Bosompem, M., Kwarteng, J.A., Ntifo- Sraw, E. Is precision Agriculture Feasible in cocoa production in Ghana? The case of cocoa High technology programme "in the eastern Region of Ghana. Department of Agricultural Economics and Extension, University of Cape Coast, Cape Coast Ghana (2010).

Caliendo, M. and Kopeinig, S. 'Some Practical Guidance for the Implementation of Propensity Score Matching', *Journal of Economic Surveys*, Vol. 22, (2008) pp. 31-72.

Clay, J. World Agriculture and the Environment. Island Press, Washington (2004).

COCOBOD. Socio-Economic Study. Final Report. Cocoa Board, Ghana (2007).

COCOBOD. Ghana COCOABOARD, poised to maintain premium quality cocoa. (2011).

Cocoa Research Institute of Ghana. Cocoa Manual, A Source Book For Sustainable Cocoa Production. (2010). pp. 20.

Dehejia, R.H. and Wahba, S. 'Propensity Score Matching Methods for Non Experimental Causal Studies'. *Review of Economics and Statistics*, Vol. 84, (2002). pp. 151-161.

Dormon, E.N.A., Van Huis, A., Leeuwis, C., Obeng-Ofori, D., Sakyi-Dawson, O. 'Causes of low productivity of cocoa in Ghana: farmer's perspectives and insights from research and the socio-political establishment'. NJAS – Wagen. *Journal of Life Science*, Vol. 52, (2004) pp. 237 –259.

Duguma, B, Gockowski, J. and Bakala J. 'Smallholder cacao (Theobroma cacao Linn.) cultivation in agroforestry systems of West and central Africa: challenges and opportunities'. *Agroforestry system*, Vol. SI, (2001) pp. 177-188.

FASDEP. Food and Agriculture Sector Development Policy. Ministry of Food and Agriculture, Government of Ghana, Accra. (2002). pp. 57

Hainmueller, J., Hiscox, J.M., and Tampe, M. Sustainable development for cocoa farmers in Ghana. Baseline survey. Preliminary Report. MIT and Harvard University. (2011).

Heckman, J., LaLonde, R. and Smith, J. The Economics and Econometrics of Active Labor Market Programs. In: Handbook of Labor Economics, Vol. III, Ed. By O. Ashenfelter, and D. Card. Elsevier, Amsterdam. (1999) pp. 1865-2097.

Hujer, R., Caliendo, M. and Thomsen, S.L. 'New evidence on the job creation schemes in Germany – a matching approach with threefold heterogeneity'. *Research in Economics*, Vol. 58, (2004) pp. 257–302.

IITA. Summary of Findings from the Child Labor Surveys in the Cocoa Sector of West Africa: Cameroon, Côte d'Ivoire, Ghana, and Nigeria. Ibadan: The International Institute of Tropical Agriculture. (2002).

Isaac, M., Timmer, V. and Quashie-Sam, S. 'Shade tree effects in an 8-year-old cocoa agroforestry system: biomass and nutrient diagnosis of *Theobroma cacao* by vector analysis'. *Nutrient Cycling in Agroecosystems*, Vol. 78, (2007) pp. 155-165.

Lee, W. Propensity score matching and variations on the balancing test, In: 3rd conference on policy evaluation. ZEW, Mannheim (Germany), 27-28 October 2008.

Ministry of Manpower Youth and Employment Ghana (MMYE). Labor Survey in Ghana-2007/2008. Executive Summary, National Programme for the Elimination of the Worst Forms of Child Labor in Cocoa (NPECLC). (2008).

MOFA. Agriculture in Ghana in 2005. Ministry of Food and Agriculture Annual Report. Accra, Ghana. (2006).

Ofori-Frimpong, K., Asase, A., Mason, J. and Danku, L. Shaded versus unshaded cocoa: Implications on Litter fall, decomposition, soil fertility and cocoa pod development. Nature Conservation and Research Center. . (2007)

Owusu, V., Abdulai, A. and Abdul-Rahmanm S. 'Non-farm work and food security among farm households in northern Ghana'. *Food Policy*, Vol. 36, (2011) pp.108-118.

Rosenbaum, P.R. Observational Studies. Springer, New York. (2002).

Rosenbaum, P.R. and Rubin, D. 'The Central Role of the Propensity Score in Observational Studies for Causal Effects'. *Biometrika*, Vol. 70, (1983) pp. 41-45.

Ruf, O.F. 'The Myth of complex cocoa Agroforests: the case of Ghana'. *Human Ecology*, Vol. 39, (2011) pp. 373-388.

Sianesi, B. 'Evaluation of the active labor market programmes in Sweden'. *The Review of Economics and Statistics*, Vol. 86, (2004) pp.133-155.

Smith, J. and Todd, P. 'Does Matching Overcome LaLonde's Critique of Non-Experimental Estimators?' *Journal of Econometrics*, Vol. 125, (2005) pp. 305–353.

STCP. Production systems and biodiversity impacts. Sustainable Tree Crops Program. Cocoa belt survey 2001/2002 Ghana. (2002).

Steffan-Dewenter, I., Priess, J.A., Mimler, M., Klein, A.-M., Schwarze, S. and Tscharntke, T. 'Linking Deforestation Scenarios to Pollination Services and Economic Returns in Coffee Agroforestry Systems'. *Ecological Applications*, Vol. 17, (2007) pp. 407-417.

Uribe, A., Mendez, H. and Mantilla, J. 'Effect of Balanced fertilization on cocoa yield'. *Better Crops International*, Vol. 15, (2001) pp. 1-3.

Wiredu, A.N., Mensah-Bonsu, A., Andah, E.K., Fosu, K.Y. 'Hybrid cocoa and land productivity of cocoa farmers in Ashanti Region of Ghana'. *World Journal of Agricultural Sciences*, Vol. 7, (2011) pp.172-178.