

# Impact of Crop Insurance On Cocoa Farmers' Income: An Empirical Analysis From Ghana

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## Research Article

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# Abstract

Risk is associated with every sector of an economy, and the pervasiveness of risk in agriculture is not new to farmers; they have, over the decades, developed ways to minimize and cope with it. The question is whether traditional strategies employed by farmers are adequate to curb unavoidable natural disasters. The goal of this study is to see how crop insurance affects cocoa producers' incomes in Ghana. A well-structured questionnaire was delivered to a sample of 600 cocoa farmers in Ghana's Ashanti region, and data was collected using a multi-stage random sampling technique. Tobit, and Propensity score-matching effect estimators were used to assess crop insurance's impact on cocoa farmers' income. The result indicates that crop insurance had a significant positive impact on cocoa farmers' income in the Ashanti region. The study recommends that the government of Ghana, with urgency, design agricultural insurance policy that can capture various farmers in the country to enhance their income and reduce poverty. Again, insurers need to promote publicity through public seminars, training, and media advertising to improve farmer awareness and knowledge of the insurance scheme.

## Introduction

In Africa, more than 70% of the population makes a living out of agriculture. The tremendous contributions of the agriculture sector to Africa, particularly Ghana, is unquestionable. In Ghana, agriculture has the propensity to eradicate poverty regarded there are pragmatic policy reforms to revamp the sector. Ghana has a total land of 23,853,900 hectares (ha), out of which about 57% is arable land for agricultural production. ISSER (2010) affirmed that agriculture accounts for about 30 per cent of the country's GDP and serves as 60 per cent of its export. Despite the positive impacts of the sector, empirical studies disclose that numerous factors limit access to it (Magri, 2002; Thaicharoen et al., 2004; Crook and Hochguertel, 2005; Del-Rio and Young, 2005; Akudugu, 2012; Agbenyo et al. 2019).

Agriculture growth is primarily determined by the crop sector, which is highly influenced by cocoa production. Cocoa is the largest subsector of the crop sector and contributes about 30 per cent to the agriculture sector in Ghana. Krishna (2007) noted that Ghana was one principal exporter of cocoa from 1911 to the 1970s before Cote D'Ivoire took over. Cocoa production to agriculture GDP increases from 13.7 to 18.9 per cent between 2000 to 2006. However, Aidoo et al. (2014) emphasize that crop production is inherently risky in Ghana due to its heavy dependence on unpredictable weather factors. Ghana's agriculture is mainly small-scale and rain-fed, making them vulnerable to risks inextricably linked with the production environment. Despite the heavily cried out literature on agricultural insurance, Nunoo and Acheampong (2014) conjectured that Ghana had no formal commercial agricultural insurance scheme until 2011.

In 2009, the German International Cooperation (GIZ) launched a project called Innovative Insurance Products for Climate Change Adaptation (IIPACC) to help Ghana deal with the socio-economic costs and hazards of climate change. Variability in rainfall patterns in Ghanaian rural communities (Stutley, 2010). The policy took effect in 2011 after the establishment of the Ghana Agricultural Insurance Pool (GAIP).

They execute an agricultural insurance system. The first drought Weather-Insurance Index (WII) product for maize was during the single cropping season in the three northern areas in the same year. According to Wehnert (2018), Disappointedly, the program faces two significant challenges, namely enrollment and claims. Thus the performance of the agricultural insurance market remains low (very few products).

Mensah (2017) claimed that the unavoidable threat that climate change poses to Ghana's agriculture can disrupt the rural source of income. Climate change and variability are threats to poverty reduction and food security. It also makes agriculture and forestry specifically vulnerable. However, Zhao et al. (2016) indicated that crop insurance could supply an income floor for disaster victims. In developed countries like Japan, a village whose paddy experienced total losses due to an extreme low-temperature event in the summer received compensations that amounted to 64% of income from the paddy in an average weather year. This insurance level covered production costs and offered a substantial fraction of the net profit from an average year (Yamauchi, 1986 and Zhao et al., 2016). Agricultural insurance is a financial strategy that allows farmers to transfer production risk to a third party by paying a premium that reflects the insurer's actual long-term cost, assuming the risks occur. To our knowledge, no study has been undertaken in Ghana to look into the impact of crop insurance on cocoa farmers' income after it was implemented.

## **Can Crop Insurance Positively Influence Farmers' Income?**

Zhao et al. (2016) investigated the impact of crop insurance on farmers' income in Inner Mongolia, China. Crop insurance does not have a major impact on farmers' income, according to the authors. They do advise, however, that a few specific adjustments to the crop insurance policy could boost its favorable effects. Most scholars in China also believe that crop insurance stabilizes farmers' incomes (Xing and Huang, 2007; Liang et al., 2008; Sun and Chen, 2011; Nie et al., 2013). Xing and Huang (2007) use historical simulation methods to estimate the effect of six government-subsidized insurance products on fiscal expenditure and farmers' income, based on production and agricultural price data from 31 provinces in China from 1978 to 2000. Results show that average agricultural incomes tend to increase or be more stable with higher coverage levels, and the subsidy rate also has a significant impact on farmers' income. Liang et al. (2008) and Sun and Chen (2011) use co-integration and Granger causality tests to explore the long-term equilibrium relationship between crop insurance and farmers' incomes. They found that crop insurance Granger causes increases in farmer income.

Luo et al. (2011) argue that agricultural insurance reduces the disparity in losses across farmers. Because of subsidy, the program provides an income transfer to farmers from the rest of the economy. Both crop insurance and government subsidization of premiums can increase the disposable income of the peasantry. Nie et al. (2013) conclude that crop insurance can mitigate risk, increase output, smooth consumption, and fight poverty. Severini et al. (2017) investigate the impact of agricultural policy on income and revenue risks on Italian farms, as well as the implications for risk management measures. Over the period 2003–2012, balanced farm-level panel data was used to construct coefficients of variation. They discovered that direct transfers always had a significant income-increasing effect. They

claim that making payments in a row reduces the risk that farmers face, allowing them to engage in riskier activities.

**Hypothesis:** *Crop insurance positively influence farmers' income*

## Methodology

### 3.1 Study area and Data

Ashanti Region is one of the regions that benefited from the crop insurance program, and farmers have been compensated, making the region a perfect one for this study. The region currently has a population size of 4,780,380, making it the highest populated region in Ghana. Out of which, 2,316,052 and 2,464,328 represent males and females, respectively (GSS, 2010). The Ashanti Region has Kumasi as its capital town and lies centrally within the country's middle belt. The region falls between longitudes 0.15W and 2.25W, and latitudes 5.50N and 7.46N (Gyasi-Agyei, 2014). In terms of landmass, the region covers 24,389 square kilometres, representing 10.2 per cent of the total land area of Ghana. Ministry of Food and Agriculture (MoFA) specified that 58 per cent of this region's occupants engage in farming, fishing, and animal husbandry (MoFA, 2011). The region is also noted for other crop productions such as Maize, Cassava, plantain, yam, cocoyam, rice, coconut, rubber, oil palm, and coffee. Owing to the brief history of the Ashanti Region, it is therefore considered suitable for the study area. Below is the map of the Ashanti Region as a study area.

### 3.2 Data

Our data are obtained from a survey administered to cocoa farmers in Ashanti Region, Ghana, in 2019. The study engages three districts, namely, Bosomtwe, Sekyere East, and Akim North District. We randomly select six cocoa production villages out of the three districts, including Nkowi, Pipie, Attakrom, Abono, Agogo, and Juasan. The district distribution of the sample is presented in Table 1 and the variable description in Table 2. The questionnaire comprises household characteristics, farm characteristics, income sources, income level and income consumption.

Table 1  
Sample Distribution

Selected Districts	Population	Percentage	Proportion to sample
Bosomtwe	93,910	35	210
Sekyere East	90,477	33	198
Akim North	87,501	32	192
Total	270,130	100	600
<i>Source: Author's calculation (2019)</i>			

Table 2  
Variable Description

Variables	Description	Measurement	Exp Sign
<b>InINC</b>	Monthly average income from farming	Continuous variable (Ghc value)	—
<b>Plns</b>	Purchase of crop insurance	Binary variable = 1(purchase), 0 (did not purchase) = Treated variable	—
<b>Gen</b>	Gender	Binary variable = 1(yes), 0 (no)	+/-
<b>Edu</b>	Educational level	Continuous Variable= (in Years)	+ / -
<b>Hsz</b>	Household size	Continuous variable (number)	+
<b>AgeF</b>	Age of cocoa farm	Continuous variable (in Years)	+
<b>Age</b>	Age of Cocoa farmer	Continuous variable (in Years)	-
<b>MS</b>	Marital status	Binary variable = 1(yes), 0 (no)	+
<b>Fexp</b>	Farming experience	Continuous variable (in Years)	+
<b>Fsz</b>	Farm size	Continuous variable (in acres)	+ / -
<b>ACIN</b>	Awareness of crop insurance	Binary variable 1(yes), 0 (no)	+ / -
<b>AC</b>	Access to credit	Binary variables = 1(have access), 0 (no access)	-
<b>EO</b>	Extension officer	Binary variable 1(yes), 0 (no)	+
<b>InSAV</b>	Savings	Continuous variable (Ghc value)	+
<b>InOTI</b>	Other income	Continuous variable (Ghc value)	+
<i>Source: Author's calculation (2019)</i>			

### 3.3 Propensity Score Matching model

According to Rosenbaum and Rubin (1983), PSM enables the correction for selection bias concerning observable characteristics that may affect policy intervention participants. According to Ashimwe (2016), impact valuation studies grieve from three major interrelated problems with significant implications for empirical outcomes. Simtowe et al. (2012) indicate that the first problem is the causal effect between treatment group and their impact on the outcome. The second problem is the omission of confounding covariates, while the final problem is purported to be counterfactual. Caliendo and Kopeinig (2008) posit that the PSM method does not solve the problem as it is perceived, hence the need to estimate the sensitivity test to investigate whether essential variables were overlooked in the evaluation and sensitivity of estimated treatment effects in the presence of unobserved heterogeneity. We employed the definition

of Rosenbaum and Rubin (1983) as the probability of being part of the treatment given pre-treatment characteristics as:

$$P(\psi) \equiv \Pr \{FI = 1 \mid \psi\} = E\{FI \mid \psi\} \dots \dots \dots \text{eqn(1)}$$

Where  $FI = \{0,1\}$  is a dichotomous variable representing whether a cocoa farmer purchased crop insurance in 2011 where Yes represent 1 and 0 otherwise,  $\psi$  is the multidimensional vector of pre-treatment characteristics of a farmer and  $P(\psi)$  is the propensity score. We estimate the impact of crop insurance on cocoa farmers' income, the average treatment effect (ATT) on cocoa farmers' who purchased crop insurance after matching was deduced. Baker (2000) and Ashimwe (2016) disclosed that the expected value of ATT is inferred as the change between expected outcome values (income of farmers) with and without treatment for farmers who purchased crop insurance in the treatment group.

$$\begin{aligned} & \mathcal{E}\{IF_{1i} - IF_{0i} \mid \vartheta_i = 1\} \\ &= \mathcal{E}[\mathcal{E}(IF_{1i} - IF_{0i} \mid \vartheta_i = 1, p(\psi_i))] \end{aligned}$$

$$= \mathcal{E}[\mathcal{E}(IF_{1i} \mid \vartheta_i = 1, p(\psi_i)) - \mathcal{E}(IF_{0i} \mid \vartheta_i = 0), p(\psi_i) \mid \vartheta_i = 1] \dots \dots \text{eqn(2)}$$

The initial step for estimating PSM is the binary estimation of factors anticipated to influence farmers' income after purchasing crop insurance. The Tobit regression model was employed to analyze the impact of crop insurance on cocoa farmers' income. The valuable econometric model for analyzing factors affecting cocoa farmers' income is the Tobit model shown in Eq. (3). The focus is on the distribution of  $(IF_{1i} \mid \vartheta_i = 1)$ ;  $i$  represents the farmers in this equation,  $1_i$  and  $0_i$  as the predictable outcomes in the two counterfactual situations of farmers who purchased and farmers who did not purchase crop insurance and  $\vartheta_i$  represent the treated group. The Tobit model presumes a latent unobserved variable  $Z_i^*$  that depends linearly on  $Y_i$  through a constraint vector  $\delta$ . There is a generally distribute error term  $\varepsilon_i$  to capture the random influence on this association. The Tobit model can be defined as:

$$Z_i = Z_i^* \text{ if } Z_i^* > 0 = 0 \text{ if } Z_i^* \leq 0 \quad (3)$$

Where,  $Z_i^*$  is a latent variable (monthly average income of cocoa farmers)

$$Z_i^* = \delta Y_i + \varepsilon_i, \varepsilon_i \sim N(0, \sigma^2) \quad (4)$$

In the Tobit model, the explanatory variables are a function of latent variables defined by observable household and agricultural factors (both exogenous and endogenous factors), as well as the error term. The empirical model is shown below.

$$\begin{aligned} \ln INC_i^* &= \delta_0^* + \delta_1^* Age_i + \delta_2^* Edu_i + \delta_3^* Gen_i + \delta_4^* AgeF_i + \delta_5^* Fsz_i + \delta_6^* AC_i + \delta_7^* Hsz_i + \delta_8^* Fexp_i \\ &+ \delta_9^* MS_i + \delta_{10}^* S_i + \delta_{11}^* OTI_i + \delta_{12}^* EO_i + \varepsilon_i \dots \dots (5) \end{aligned}$$

Where,  $\ln INC_i^*$  = the log of the monthly average income of cocoa farmers,  $\varepsilon_i$  is the error term, and

$\delta_0^*, \delta_1^*, \delta_2^*, \delta_3^*, \delta_4^*, \delta_5^*, \delta_6^*, \delta_7^*, \delta_8^*, \delta_9^*, \delta_{10}^*, \delta_{11}^*$  and  $\delta_{12}^*$  are the vector of parameters for the control variables that must be estimated.

## Empirical Results And Discussion

### 4.1 Empirical Results

The study considered cocoa farmers' who purchased crop insurance as the treatment group, and those who did not purchase are referred to as the control group. In order to have a thorough investigation, we estimate the descriptive statistic in three main categories. Thus, we consider the entire sample, the treatment, and the control group. In addition to providing basic descriptive statistics for each variable employed in the study, we compare the means of farmers who purchased crop insurance against those who did not.

Evidence from the fundamental descriptive analysis indicates the systematic differences between treatment and control group. From the descriptive in Table 3, we can deduce that Income, Age, Marital status, Education, awareness of crop insurance, age of farm, extension officer and savings recorded a significant difference between treatment and control groups. In contrast, other variables did not exhibit any significant difference between the two groups. However, a focus on our interest variable (income) implies that farmers who had the opportunity to participate or purchase crop insurance improved their income compared to farmers who did not purchase crop insurance.

This finding is consistent with Zhao et al. (2016). They identified a difference among farmers who purchase crop insurance to have an average income than farmers who do not pay for it. They, however, likewise disapproved of the findings on the basis that the DiD estimator is biased. They equally attribute the increment in farmers' income to be nominal since it is not inflationary adjusted as in the case of this study. This finding cannot be reliable since it has been confirmed that there is an imbalance among the distributions. Hence, the study needs to employ the propensity score matching method to reduce the bias identified among the treated and control group based on the observable covariates and better compare the groups.

Table 3  
Descriptive statistics

Variables	All		Uninsured		Insured		M(c) – M(t)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t
InINC	7.40	.566	7.374	.528	7.450	.630	-2.633**
Gen	1.32	.468	1.309	.463	1.347	.477	-0.922
Edu	1.88	.823	1.817	.831	2.020	.791	-2.858**
Hsz	5.80	1.799	5.807	1.741	5.796	1.919	0.070
AgeF	7.23	4.420	7.005	4.220	7.679	4.786	-1.754*
Age	43.99	6.405	43.931	6.402	44.117	6.425	-0.335
MS	2.37	.968	2.275	.897	2.561	1.077	-3.429***
Fexp	14.06	5.914	14.205	5.976	13.760	5.788	0.865
Fsz	11.95	4.699	12.069	4.927	11.699	4.191	0.905
ACIN	1.58	.494	1.629	.484	1.481	.501	3.416***
AC	1.67	.469	1.668	.472	1.672	.471	-0.104
EO	2.13	1.078	2.230	1.093	1.923	1.017	3.296***
InSAV	6.43	.420	6.379	.453	6.512	.349	-2.779**
InOTI	7.26	.554	7.249	.588	7.278	.479	-0.555
Source: Field Survey, 2019							

## 4.2 Factors that influence cocoa farmers' income

The results of Tobit regression are presented in Table 4. Our result indicated that farmers' age coefficient had a negative effect on their income and was statistically significant. The age of a cocoa farmer negatively influences the willingness to pay for crop insurance. An additional year in the age of a cocoa farmer will negatively influence his or her income. The probability is -0.53, all other things being equal. The result is consistent with previous studies such as Falola et al. (2013), Wairimu et al. (2016), Okoffo et al. (2016), and Langyintuo and Mulugetta (2005). The marital status of cocoa farmers had a significant positive impact on their income, as expected. This estimate is statistically significant at the 10% level. The possible interpretation of this outcome is that married farmers may have their spouses engaging in different work to reduce the burden on their family income. Danso-Abbeam (2014) conjectures that married farmers have responsibilities, compel them to engage in activities that reduce their vulnerability to risks. Access to credit had a significant negative impact on farmers' income and was statistically significant at the 10% level. Not surprising as the majority of the respondents in the study area indicate

that they lack access to credit. Access to credit is a significant problem for most African farmers as financial institutions find it risky to loan farmers. This result implies that the non-accessibility of credit leads to a decrease in farmers' income by a probability of -0.021, all things being equal. Savings had a positive relationship with farmers' income. It implies that a unit increase in the savings attitude of farmers leads to an increase in farmers' income by 26.4%.

Table 4  
Factors that influence Cocoa Farmers' Income

Variables	Coef.	Std. Err	Marginal Effect	z	P >  z
Gender	-.070	.756	-.012	-0.93	0.352
Education	-.059	.050	-.014	-1.19	0.233
Household size	-.024	.017	-.018	-1.42	0.156
Age of Farm	-.003	.007	-.003	-0.46	0.642
Age	-.009	.005	-.053	-1.80	0.072*
Marital Status	.080	.046	.025	1.74	0.081*
Farm experience	-.001	.005	-.002	-0.16	0.874
Farm size	-.008	.007	-.013	-1.25	0.210
Aware Crop insurance	.031	.067	.006	0.46	0.647
Access to Credit	-.114	.066	-.021	-1.72	0.085*
Extension service	-.161	.037	-.038	-4.43	0.000***
Log (Savings)	.264	.072	.226	3.69	0.000***
Log (off-farm income)	-.043	.054	-.041	-0.79	0.427
_cons	7.144	.702		10.18	0.000***
F(15, 237) = 5.03 Prob > F = 0.0000 and Pseudo R <sup>2</sup> = 0.1639					
Inferences: *** p < 0.01; ** p < 0.05; * p < 0.1					
<i>Source: Author's computation based on survey data (2019)</i>					

## 4.3 The impact of crop insurance on cocoa farmers' income

Figure 2 below displays the distribution of the estimated propensity score standard in the region of common support for cocoa farmers' who purchased crop insurance from the year of its implementation and cocoa farmers who did not purchase crop insurance since its implementation.

Before a PSM estimation, it is necessary to check for possible violations of some conditions; a typical example is the overlap assumption. There is a need for both treated and control groups to satisfy the

common support condition. Thus, according to Caliendo and Kopeining (2008), both groups must be within the standard support region. Evidence from the visual assessment of Fig. 2 above on the density distribution between the groups indicates that the treated and control group are within the region of common support. From Fig. 2 above, the upper region in red implies the distribution of the treated group, whereas the bottom in blue represents the control group. The y-axis denotes the propensity scores for the two groups. By implication, each cocoa farmer had a positive probability of being a buyer of crop insurance or not a buyer of crop insurance. It validates the common support assumption that necessitates each cocoa farmer who purchased crop insurance to have a corresponding non-crop insurance buyer as a match (Austin, 2011; Ashimwe, 2016).

Matching is an essential estimation for treatment effect to remove over bias and estimate the treatment effect using observational data (Baser, 2006). The goal of propensity score estimation is to balance the covariate distribution in the treated and control groups (Rosenbaum & Rubin, 1983). Propensity score matching employs a predicted probability of the treated and control grouped in this case, cocoa farmers who purchased crop insurance and did not purchase crop insurance, respectively. In order to maintain consistent matching between the results, four different techniques for the estimation of the propensity score matching was employed, namely, Nearest Neighbor (NNM), Radius (RM), Kernel (KM) and Local linear regression matching (LLRM). With the NNM method, the study seeks to order treated and control groups randomly. Then select the first cocoa farmers who purchased crop insurance and find one cocoa farmers who did not purchase crop insurance with the closest propensity score (LaLonde, 1986; Baser, 2006).

Regarding the above, the study employed all the four techniques mentioned above to estimate the differences between the covariates of cocoa farmers. With RM estimation, each treated element was matched only with the control element whose propensity score falls in a predefined neighbourhood of the propensity score of the treated unit (Dehejia & Wahba, 2002; Baser, 2006). According to Baser (2006), the pros of the NR method are that it uses only the number of judgment elements accessible within a predefined radius, hence allowing for the use of extra elements when suitable matches are available and fewer units when they are not. One disadvantage of this method is the decision of precise radius to use compared to KM. All treated elements are matched with a weighted average of all controls, with weights inversely proportional to the distance between the propensity scores of the farmers who purchased and did not purchase the insurance. All cocoa farmers who did not purchase crop insurance contribute to the weights achieving lower variance. According to Caliendo and Kopeining (2008), this can be considered as a plausible counterfactual.

These four methods have evidentially portrayed no systematic differences in the distribution of covariates between treated and control groups. Insignificant p-values of the likelihood ratio and a reduction in bias after matching for the covariates balance tests, according to Rosenbaum and Rubin(1985), should be used to specify the estimation. Caliendo and Kopeining (2008) later posit that variances are predictable before matching; nevertheless, there should be a balance in the treated and control group after matching the covariates, indicating that no significant difference is found. Evidence

from the current study shows no significant difference found between the treated and control group after matching.

Table 5 below presents summary statistics, including the standardized mean, median bias coupled with the pseudo-R<sup>2</sup>. According to Rosenbaum and Rubin (1985), the standardized mean and median bias differences between the treated and control groups should not be more significant than 20%. The difference between the standardized mean and median bias when greater than 20% is considered large. Evidence from Table 5 indicates that among the four matching algorithms employed in the covariate balancing tests, radius matching and kernel-based matching stands out to be the appropriate matching algorithm. This assertion is based on the reduction rate of standardized mean and median bias. The mean bias before matching for all the four matching techniques is 11.5, which has reduced to 3.8, 2.2, 2.1 and 3.6 after matching for the nearest neighbour, radius, kernel-based and local linear regression matching, respectively. The median bias also reduces from 8.5 to 3.3, 2.1, 1.9 and 3.3 for the nearest neighbour, radius, kernel-based, and local linear regression matching. Based on the results, the appropriate matching techniques we adopt is radius and Kernel-based propensity matching. Considering the mean and median biases of the RM and KM are below 10%, indicating a good match between cocoa farmers who purchased and did not purchase crop insurance.

Again, pseudo-R<sup>2</sup> of the RM and KM before and after matching indicates the probability that farmers who did not purchase crop insurance are likely to purchase (Sianesi, 2004).

Before matching, the pseudo-R<sup>2</sup> was 0.037, but it dropped to 0.001 for RM and KM, which is very low and significant enough to support the assumption that there are no variations in the distribution of variables between the treatment and control groups. As a result, this study asserts that the matching method was able to effectively balance the circulation of covariates between the treated and control groups, and there is a reliable counterfactual on the assertion that this study achieved low pseudo-R<sup>2</sup> values, insignificant p-values, low standardized mean bias, and high total bias reduction. These findings indicate that there is no consistent difference in the covariate distribution of income between the treatment and control groups. As a result, the crop insurance intervention in the community could result in a unit difference in farmers' income between the two groups with the possibility of increasing.

Table 5  
Summary of covariates balancing tests for Matching Algorithms

Types Matching algorithms	Pseudo-R <sup>2</sup> Before Matching	Pseudo-R <sup>2</sup> After Matching	P > Chi <sup>2</sup> before	P > Chi <sup>2</sup> After	Mean bias before	Mean bias After	Median bias before	Median bias After
NNM	0.029	0.004	0.037	0.997	11.5	3.8	8.5	3.3
RM	0.029	0.001	0.037	1.000	11.5	2.2	8.5	2.1
KM	0.029	0.001	0.037	1.000	11.5	2.1	8.5	1.9
LLRM	0.029	0.040	0.037	0.999	11.5	3.6	8.5	3.3

*Source: Author's computation based on survey data (2019)*

The treatment effect (ATT) of crop insurance intervention on cocoa farmers' income are presented in Table 6 below. Table 6 reports the treatment effects based on nearest neighbour, radius and kernel matching algorithm. The results for comparison of cocoa farmers' who purchased and did not purchased crop insurance are statistically insignificant but in the anticipated positive direction for the neighbour, radius and kernel matching estimations. This implies that farmers' participation in crop insurance has a positive impact on farmers' income. The interpretation of this result would imply that a cocoa farmer who purchases crop insurance tends to earn a higher income than their counterparts who did not purchase crop insurance by 8.3% and 6.8%, respectively. The result is consistent with Zhao et al. (2016) where they established that there is no significant impact of crop insurance on farmers' income inner Mongolia in China. The estimation also agrees with Varadan and Kumar's (2012) study, which revealed that high use of farm inputs and production risks are absorbed by agricultural insurance. Nahvi et al. (2014) found a significant positive relationship between income and agricultural insurance in Iran. Similarly, Yanuarti et al. (2019) also found a positive impact of crop insurance on Indonesian farmers' income.

Table 6  
Impact of crop insurance on cocoa farmers' income

Dependent variable Farmers' income					
Matching Algorithms	Treated	Control	ATT	Bootstrap S.E	T
NNM	194	102	0.083	0.077	1.083
RM	4	317	0.776	0.224	3.463***
KM	194	384	0.068	0.052	1.309

*Source: Author's computation based on survey data (2019)*

## Conclusion And Policy Implications

The study aimed to investigate the impact of crop insurance on cocoa farmers' income in the Ashanti region. The program began in 2011 in the Ashanti region, and the study commenced in 2019. The estimates show that household size, gender, age of farm, access to credit and farm labour negatively influence farmers income. Farmer's age and farm experience had a negative effect on income but were statistically insignificant. The marital status of cocoa farmer's had a significant positive impact on farmers' income. The study conjecture that purchasing crop insurance for a cocoa farm leads to an increase in farmers income. The findings agree with Zhao et al. (2016), Varadan and Kumar (2012), Nahvi et al. (2014) and Yanuarti et al. (2019). As evidence from the findings that crop insurance has a positive impact on farmers' income, the study recommends that the government of Ghana design agricultural insurance policy that can capture a wide range of farmers in the country with a matter of urgency. Government funding usually takes the form of a direct premium subsidy to the producer. This usually is common in European nations such as the Czech Republic, France, Austria and Slovenia. These countries have been prosperous in having a well-developed agricultural insurance system for their farmers. The government of Ghana should adopt such policies and intervene in the policy in the country. The findings of the study are strong enough to suggest that farmers' income increased as a result of their participation in crop insurance; as a result, practical steps are needed to promote farmers' desire to participate in insurance programs. Farmers must be educated on the need of crop insurance for farming operations, either through the insurer's aggressive marketing of the insurance program or through cooperative activities. In this sense, cooperative societies in Ghana need to be encouraged so that they may effectively advocate for their members and disseminate information.

## Declarations

**Author Contributions:** W.A.; Conceptualization, data curation, formal analysis, investigation, G. N., Literature review and data curation, Y.J.; supervision, review and editing. All authors have read and agreed to the manuscript.

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Competing Interests: The authors declare that they have no competing interest

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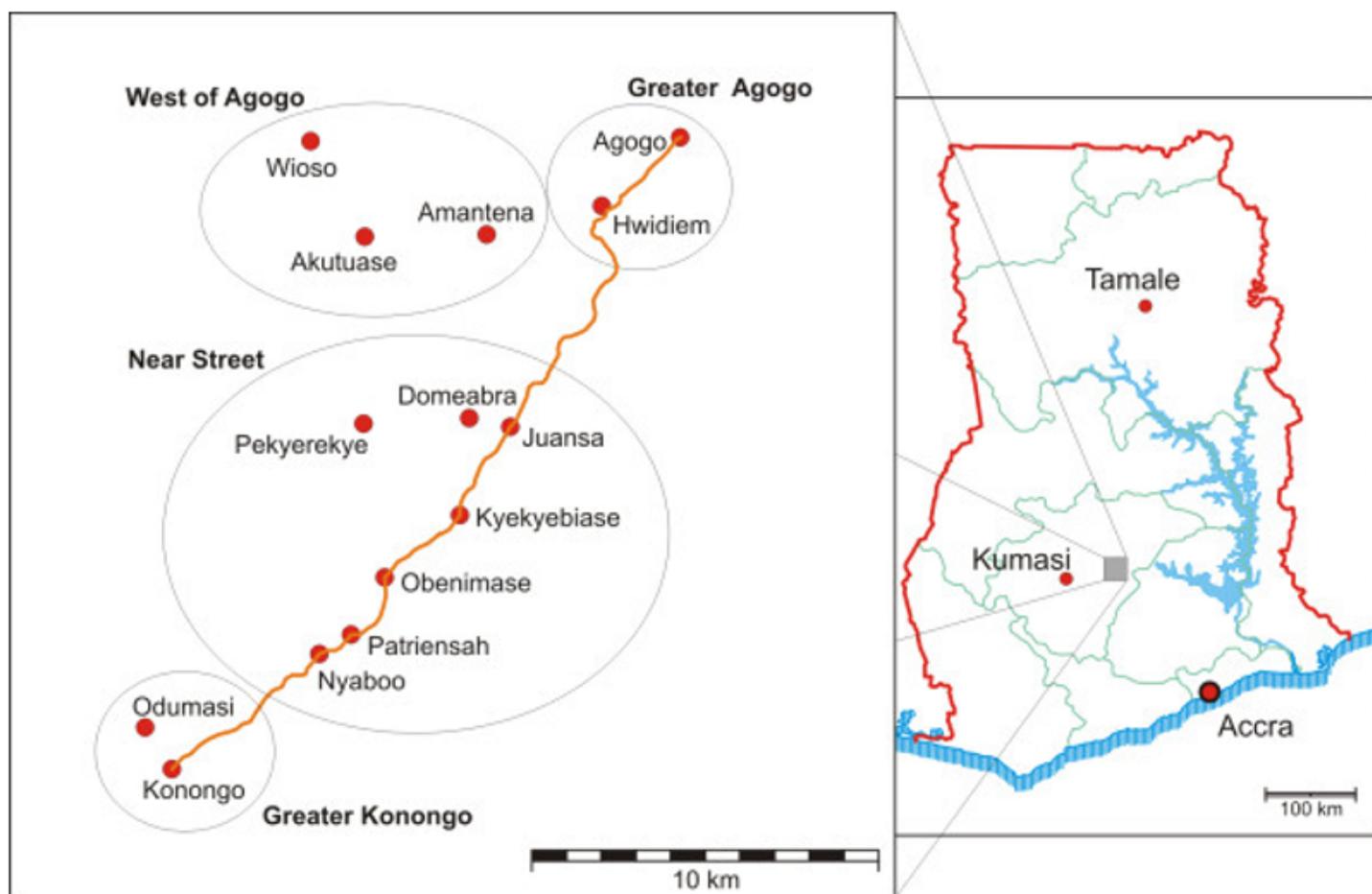
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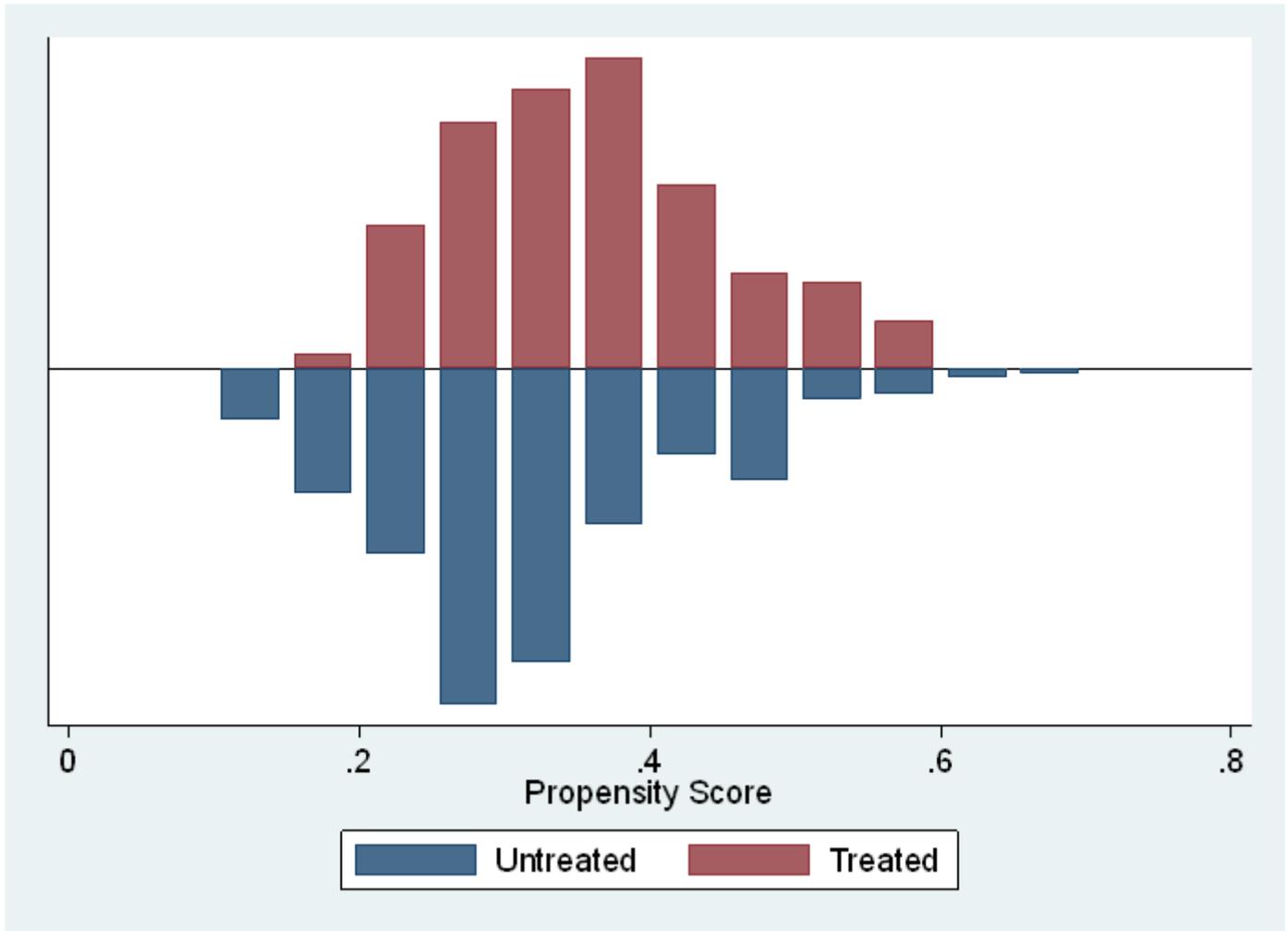
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## Figures



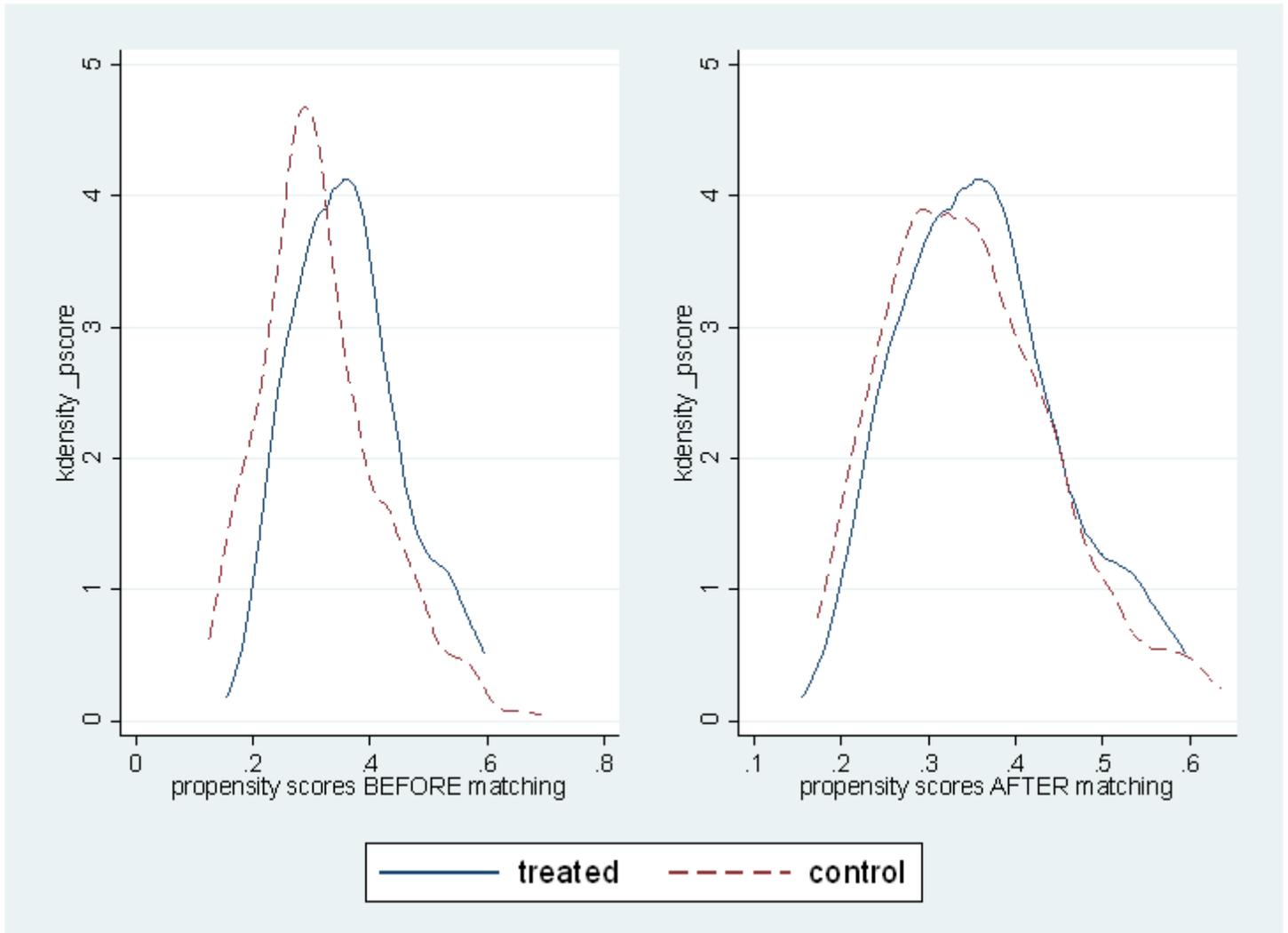
**Figure 1**

Map showing the study area (Ashanti Region)



**Figure 2**

Displays the distribution of the estimated propensity score standard in the region of common support for cocoa farmers' who purchased crop insurance from the year of its implementation and cocoa farmers who did not purchase crop insurance since its implementation.



**Figure 3**

Graphical presentation of Propensity scores Before and After Matching