Indigenous technology Adoption and Poverty Reduction in Rural Nigeria

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Abstract
This paper evaluates the potential impact of indigenous agricultural technology adoption on poverty of farm households. It does so through an empirical investigation of the relationship between adoption of indigenous innovation, of the crop protection type, and wellbeing of farm households in Nigeria. As the indigenous innovation adoption is not randomly assigned but there is ‘self-selection into treatment’, the paper tackles a methodological issue in assessing the causal effect of the innovation on farm-household wellbeing through the non-parametric matching analyses applied to a cross sectional survey data. It pursues a targeted evaluation of whether adopting the indigenous technology improves farmers income and subsequently their well being. The result revealed a positive and significant effect of adoption on adopter’s income suggesting that there is a large scope for enhancing the role of indigenous agricultural innovation in ‘directly’ contributing to poverty alleviation.

Keywords: Indigenous; Adoption; Poverty Reduction; Propensity score matching;
JEL classification: Q12, Q16, H43

Introduction
Reduction of poverty among rural poor remains an important issue because of its relevance to economic development theory. The projections that over 60% of the rural populace will continue to remain poor in 2025 (Mendola, 2007) suggest a need to focus on poverty reduction strategies of rural households. In Nigeria, Most rural households engage in agriculture which contributes significantly to the Gross Domestic Product (GDP) and employing about 77 percent of the working population (CBN and NBS 2006). World Bank in their analysis of the poverty in Nigeria noted that poor families are in higher proportion in farming households who are mainly in the rural areas; regions where agriculture is the major source of employment. Since poverty is widespread and is largely rural, increase in agricultural productivity has therefore being suggested as the main pathway out of poverty (Alene et al. 2005). However studies revealed that poverty is rarely due to insufficient production but rather to sustainability of smallholder farming, disregard for indigenous knowledge (IK), local agricultural resource management and utilization of the poor factor endowment for improved income earnings and well-being (Wolfgang and Wanyama, 2006; WDR, 2008).
In rural Nigeria, the use of indigenous practices is mostly relevant in the management of pests and diseases of crops. Damage by pests and diseases has been identified as one of the visible factors responsible for the decline in yield of agricultural output in the tropics (Adejumo, 2005). Although application of synthetic pesticides has been found to be effective in controlling the pests and diseases of cocoa, its usage is generally fraught with problems of undesirable side effects and food chain involvement. Many pesticides pose substantial short and long term health risks, occupational and health hazards, resistance and secondary pest outbreak (Asogwa and Dongo, 2009; Sosan et al., 2010).

The adoption of pest management alternative; Siam weed (*Eupatorium odoratum*) Soap solution, has generated increased interest in the literature (e.g. Tijani and Omondiagbe, 2006; Mugisha-Kamatenesi et al. 2008). Although several studies have examined the impact of innovation adoption and diffusion decisions of farm households in both developed and developing countries, there is dearth of literature on impact of adoption of alternative pest management method on outcomes such as yield, income and consequently the poverty status of farm households. The few studies that have carried out similar analyses have often ignored the fact that technology adoption is not randomly assigned but that there is self-selection into treatment. Ignoring this issue in the estimation procedure leads to biased estimates and wrong policy recommendation (Abdulai and Binder, 2006).

Self-selection emerges because of the fact that farmers select themselves into treatment. This study employs a non-parametric approach to examine the impact of household adoption decisions on potential outcomes. Specifically, the study examines the impact of the adoption decision of Siam Weed Soap Solution on yield, income and poverty status among cocoa farmers in South-western Nigeria. A propensity score model is employed to control for self-selection that normally arises when technology adoption is not randomly assigned and self-selection into adoption occurs.

**Crop pest control strategies in Nigeria**

Application of synthetic pesticides is the most widely adopted method of crop insect pest and disease control in Nigeria because of their quick and effective action. It has been estimated that about 125,000-130,000 metric tonnes of pesticides are applied every year in Nigeria. In 1991, cocoa pesticides accounted for about 31% of the total agro-chemical market of which fungicides accounted for 65% and insecticides 35% (Ikemefuna, 1998). According to Asogwa and Dongo, (2009) pesticide use in Nigeria has been on the increase ever since its introduction in early fifties especially for cocoa production. Nigerian cocoa production is still dependent on synthetic pesticides to attain acceptable levels of crop production.

Over reliance on synthetic chemicals to control pests has given rise to a number of problems, which may affect the food chain and impacting negatively on biological diversity. The wrong use of synthetic pesticides can lead to secondary outbreaks of pests that are normally under natural control resulting in their rapid proliferation. There have also been cases of pests becoming tolerant or resistant to pesticides, resulting in the use of double and triple application rates (Stoll, 2000). Besides, other problems such as health hazards, undesirable side effects and environmental pollution caused by the continuous use of synthetic chemical pesticides (Nas, 2004), have renewed interest in the application of botanical pesticides for crop protection.
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Adejumo (2005) reported that local herbs and constituents of plant materials offer cheap and safer control for those categories of farmers who cannot afford the present high cost of synthetic pesticides. Also, Adejumo (2000) reported the potentials of *Chromolaena odorata* and *Piper guineense* in controlling black pod disease. Tijani and Omondiagbe, (2006) also reported the use of Siam weed (*Eupatorium odoratum*) among cocoa farmers in Osun-state for crop protection. Solution made of Siam weed, alum, black soap and water – called Siam Weed Soap Solution (SWSS) was experimented with. The solution was prepared, tested and found to be preliminarily effective on fungus diseases of the cocoa pod. It also reported farmer in Osun-state who between 2004 and 2007 tested the solution and find it very effective in controlling cocoa pests, with no visible side effects on the crop. Siam Weed Soap Solution has also been reported to have demonstrated prominent advantages over copper sulphate in the control of cacao pests and diseases as well as other similar innovations such as kerosene soap solution, neem (*Azadiracta indica*) soap solution and tobacco (*Nicotiana tabacum*) soap solution against the pests and diseases of cacao in Osun State, Nigeria.

**Theoretical framework**

There a number of reasons why the adoption of agricultural technology may influence outcomes such as output and net returns. However, it may be difficult to simply attribute the observed differences in the outcomes between adopters and non-adopters to the adoption of the technology. Ideally, experimental data gathered through randomization, would provide information on the counterfactual situation that would solve the problem of causal inference. As this is not the case, a problem of missing data exist (Blundell and Costa Dias, 2000) which creates the need to resort to a direct effect of technology adoption from the variation in outcomes across the farm households. As noted by Ichino (2001), in seeking to isolate the technology effect from other household and farm characteristics, certain statistical pitfalls of cross-sectional inference need to be avoided. Quite significant is the issue of self-selection, whereby the decision of households to adopt or not to adopt the technology may be associated with the net benefits from adoption. Specifically, the relationship between a new technology and an outcome such as output and net return could be interdependent. Thus, technology adoption can help increase output and net return, whereas higher output and net return through the income effect can influence the adoption of new technologies. Thus, treatment assignment is not random, with the group of adopters being systematically different. The interest in the current article is not only the correlation between adoption and the outcomes but also what it reveals about the causation (Ichino, 2001).

**The propensity score matching method**

A propensity score model controls for self-selection that normally arises when technology adoption is not randomly assigned and self-selection into adoption occurs. The main parameter of interest in non-experimental framework is the average treatment effect for the treated population (ATT), expressed as

\[
\tau_{ATT} = E(Y_1 - Y_0 | D = 1) = E(Y_1 | D = 1) - E(Y_0 | D = 1),
\]

where \( Y_1 \) denote the value of the outcome when the household adopts the mulching technology (1), and \( Y_0 \) is the value of the same variable when the household does not adopt (0). The problem that arises...
with un observability is by virtue of the fact that \( E(Y_1 \mid D = 1) \) can be estimated but not \( E(Y_0 \mid D = 1) \). Although \( \tau = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 0) \) can normally be estimated, it is potentially a biased estimator of \( \tau_{ATT} \). This kind of bias is a central concern in non-experimental studies (Smith and Todd, 2005).

The propensity score matching (PSM) model has been suggested by Rosenbaum and Rubin (1983, 1985) to account for sample selection bias due to observable differences between treatment and comparison groups (Dehejia and Wahba, 2002). PSM controls for self-selection by creating the counterfactual for the group of adopters. PSM constructs a statistical comparison group by matching every individual observation on adopters with individual observations from the group of non adopters with similar characteristics. In effect, the matching procedure creates the conditions of a randomized experiment in order to evaluate a causal effect as in a controlled experiment (Rosenbaum and Rubin, 1983). To achieve this, the matching approach employs the conditional independence assumption (CIA), which states that technology selection is random and uncorrelated with the outcome variables, once we control for \( Z \).

The CIA or “strong unconfoundedness” can be given as

\[
Y_I, Y_0 \mid ID | Z
\]

The effect of adoption on the outcome variables can then be expressed as

\[
\tau_{ATT}(Z) = E(Y_1 - Y_0 | Z) = E(Y_1 \mid D = 1, Z) - E(Y_0 \mid D = 0, Z).
\]

The average adoption effect can then be represented as

\[
\tau = E\{\tau(Z)\}.
\]

Under the condition of random technology adoption, outcomes for similar households in different adoption status (i.e., adopters vs. non-adopters) can be compared, with similar households’ defined according to the values of \( Z \). The propensity score reduces the dimensionality of the conditioning problem associated with \( Z \) by comparing households with similar probabilities of adopting the new technology, given the relevant controls \( Z \) (Dehejia and Wahba, 2002). The conditional probability to adopt the new technology, given the control of \( Z \), is as follows:

\[
p(Z) \equiv P(D = 1 \mid Z) = E(D \mid Z)
\]

where \( D = \{0, 1\} \) is the indicator of exposure to treatment, and \( Z \) is the multidimensional vector of pre-treatment characteristics. As indicated above, the propensity score is a function such that the conditional distribution of \( Z \), given \( p(Z) \), is the same in both groups, that is, conditional to \( p(Z) \), \( Z \) and \( D \) are independent. This balancing property of propensity score can be expressed as \( DZ \mid p(Z) \) (Lee, 2008).

Hence, if the unconfoundedness assumption holds, all biases due to observable components can be removed by conditioning on the propensity score (Imbens, 2004). Given the propensity score, which can be estimated by any standard probability model, the ATT can be estimated under the CIA as follows (Becker and Ichino, 2002):

\[
\tau_{ATT} = E\{Y_1 - Y_0 \mid D = 1\}
\]

\[
= E\{E\{Y_1 - Y_0 \mid D = 1, p(Z)\}\}\}
\]

\[
= E\{E\{Y_1 \mid D = 1, p(Z)\}\}
\]
$- E \{Y_0|D = 0, p(Z) \mid D = 1\}$.

Another important requirement for conducting the matching method is the common support condition (CSC). Heckman et al. (1997) point out that it is only in the overlapping subset of the comparison and treatment groups that comparable observations can be matched. The overlap condition is defined as follows:

$$0 < P(D = 1 \mid Z) < 1.$$ 

By the overlap condition, the propensity score is bounded away from 0 and 1, excluding the tails of the distribution of $p(Z)$. This assumption ensures that persons with the same $Z$ values have a positive probability of being both adopters and non-adopters. If there are regions where the support of $Z$ does not overlap for the different groups, matching is only justified when performed over the common support region. A violation of the CSC is a major source of bias due to comparing incomparable individuals (Heckman et al., 1997). Individuals that fall outside the region of common support have to be discarded and so the treatment effect cannot be estimated. After estimating the propensity scores, the next stage involves matching the adopters with non-adopters of similar propensity scores. Several techniques have been suggested in the literature to find the “closest” neighbor as a matching partner. Five approaches have been commonly used to match treatment and control groups. Although all the approaches should normally yield the same results asymptotically, the choice of a matching approach could become important in small samples (Heckman et al., 1997). These approaches include nearest-neighbour matching; kernel-based matching, stratified matching, and radius matching. All these are based on the propensity score. The nearest neighbour simply identified for each household the “closest twin” in the opposite technological status; then it computes an estimate of the technological effect as the average difference of household’s outcome between each pair of “matched households”. The kernel-based matching estimator is more flexible than the former with respect to the specification of the propensity score. It follows the same steps as the nearest neighbour but the “matched household” is identified as the weighted average of all households in the opposite technological status within a certain propensity score distance, with weights inversely proportional to the distance.

**Methodology**

This study was carried out in Osun state. The state is located in south-western Nigeria, and lies within latitude $7.0^\circ$ and $9.0^\circ$ N and longitude $2.8^\circ$ and $6.8^\circ$ E. The state covers a total land area of approximately 8,602 km$^2$. It is characterized by two-peak rainfall regimes with a short August break, which is considered beneficial to cocoa production. This also makes the area more susceptible to *Phytophthora palmivora*. The average rainfall ranges from 1125mm in derived savannah to 1475 mm in the rain forest belt. The mean annual temperature ranges from 27.2$^\circ$C in the month of June to 39.0$^\circ$C in December. The state comprises three agro- ecological zones: rain forest (Ife/Ijesa), derived savannah (Osogbo) and savannah (Iwo) zones. The state vegetation is characterized by secondary forest and in the northern part, the derived savannah mosaic predominates.

The soil type of the study area belongs to the highly ferruginous tropical red soils associated with basement complex rocks. As a result of the humid forest cover in the area, the soils are generally deep and are of two types, namely, deep clayey soils formed on low smooth hill crests and upper slopes; and
the sandy hill wash soils on the lower slopes. The well drained clay soils of the hill crest and slopes are very important, because they provide the best soils for cocoa and coffee cultivation in the state. The lighter loams are more suitable for cultivating the local food crops, such as yam, cassava and maize. Osun’s economy is based mainly on agriculture. The area is mainly agrarian in outlook with larger percentage of its people being farmers. Their other occupations include making of hand-woven textiles, tie and dye clothes, leather work, calabash carving and mat-weaving. Food crops grown in the area include maize (*Zea mays*), yams (*Dioscorea spp.*), cassava (*Manihot esculenta*), Cocoyam (*Colocasia spp.*), and rice (*Oryza sativa*). The permanent crops include cocoa (*Theobroma cacao*), kola nut (*Cola nitida* and *C. acuminata*), plantain and bananas (*Musa spp.*), oil palm (*Elaeis guinensis*) and citrus (*Citrus spp.*). These crops are usually mixed or intercropped. The varieties of cocoa commonly grown in the area are Amazon F3 and other hybrids.

A multi-stage sampling procedure was employed to select 300 cocoa farmers in the study area. At the first stage, the cocoa farmers in the state were purposively selected. The second stage involved the stratification of the farmers into two – comprising adopters of pest management innovation method and non-adopters of the method. The third stage involved random selection of one hundred and fifty cocoa farmers from each of adoption categories. Cross sectional data were collected from the cocoa farmers using a structured questionnaire. Data collected included socio-economic characteristics of the farmers, factors influencing adoption, expenditure and income of the cocoa farmers. The data were analyzed using propensity score matching method and poverty depth analysis. The description, measurement of the study variables are presented in Table 1.

*Table 1: Description and measurement of the study variables*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Age of the farmers</td>
<td>Years</td>
</tr>
<tr>
<td>Hhsize</td>
<td>Household size</td>
<td>Number of people living under the same roof</td>
</tr>
<tr>
<td>Eduq</td>
<td>Level of education</td>
<td>Years</td>
</tr>
<tr>
<td>Fmsiz</td>
<td>Farm size</td>
<td>Hectares (ha)</td>
</tr>
<tr>
<td>Fmexp</td>
<td>Farming experience</td>
<td>Years</td>
</tr>
<tr>
<td>Membership of association</td>
<td>The question is asked if the farmer is a member of the crop association to measure the social capital</td>
<td>Dummy (1 if the respondent is a member; 0 otherwise)</td>
</tr>
<tr>
<td>Income</td>
<td>Monetary value (₦; ₦153 =1$ as at time of study) of the produce measured as quantity produce multiply by the price</td>
<td>Naira value</td>
</tr>
</tbody>
</table>
Results and Discussion

The analysis of the correlations between independent variables to detect the possibility of multicollinearity is presented in Table 2. The result reveals that none of the variables is highly correlated. For example, the highest correlation coefficient exists between age and farming experience. The value is 0.7431 and it is expected to be within that range giving the close relationship between age and experience. It should however be noted that inferences cannot be made from correlation results because it assumes symmetrical relationship between correlating variables. To further examine collinearity, a variance inflation factors (VIF) test was conducted. VIF can detect whether collinearity exists or not (no collinearity exists if the VIF is below 10). Table 2 shows that the VIF values of the independent variables range from 1.62 to 2.76 and have a mean VIF of 2.41. Thus, it can be concluded that no collinearity exists between these variables.

Table 2: Correlation matrix of the independent variables

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Hhsize</th>
<th>eduq</th>
<th>fmsiz</th>
<th>fmexp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hhsize</td>
<td>0.4953</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eduq</td>
<td>-0.4487</td>
<td>-0.5056</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>fmsiz</td>
<td>0.5838</td>
<td>0.5610</td>
<td>-0.7028</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>fmexp</td>
<td>0.7431</td>
<td>0.4047</td>
<td>-0.5777</td>
<td>0.5361</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Source: Data analysis, 2011

Table 3: Results of multicollinearity diagnosis

<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>2.76</td>
</tr>
<tr>
<td>Hhsize</td>
<td>2.72</td>
</tr>
<tr>
<td>eduq</td>
<td>2.54</td>
</tr>
<tr>
<td>fmsiz</td>
<td>2.41</td>
</tr>
<tr>
<td>fmexp</td>
<td>1.62</td>
</tr>
<tr>
<td>Mean VIF</td>
<td>2.41</td>
</tr>
</tbody>
</table>

Source: Data analysis, 2011.
Socio Economic Characteristics of the Respondents

A summary of the socio economic characteristics of the sampled respondents in the study area revealed that actual mean estimates for socio-economic variables did not show much variation between adopters and non-adopters (See Table 4). However, significant differences (5% level) were found in the estimates obtained for some variables between the different groups of adopting status and the study area in general. These include household size, farm size and years of farming experience. There were no significant differences between the age and years of education of the two different groups of farmers. A majority of the respondents in the study area were ageing, with low level of education. However, age was not statistically significant between the two groups of farmers. The results indicated that cocoa farming was not predominant among young and energetic farmers.

The mean household size of adopting households was comparatively low and statistically different to that of non-adopters of pest management innovation method. The average household size was 6 for adopters and 8 for non-adopters which implies that the cocoa farmers have relatively large family size in the study area.

Farm size of adopters and non-adopters of pest management innovation method significantly differed. The adopters had average cocoa farm size of 6.85 hectares while the non-adopting farmers had average of 4.87 hectares. The mean farm size for all the respondents was 5.87ha. Years of farming experience was found to be statistically different between the two groups of farmers. Also, the descriptive results indicated that the farmers had long years of experience in cocoa farming. The average year of experience was 25.34 and 29.18 for adopters and non adopters, respectively. The average year of experience for all the respondents was 27.26. The level of education for the two groups of farmers was low and statistically insignificant. The results also showed a statistically significant difference between yields per hectare of the farmers belonging to different adoption status. The average net yield per hectare of the adopters and non-adopters equals 2003.5 kg and 1407.5 respectively. The findings reveal a statistically significant difference in the income of the adopters and non-adopters. The income represents the farm income of the cocoa farmers in the study area.

Table 4: Socioeconomic Characteristics of Respondents

<table>
<thead>
<tr>
<th>Variables</th>
<th>Adopters</th>
<th>Non-adopters</th>
<th>All samples</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>57.9</td>
<td>57.16</td>
<td>57.53</td>
<td>1.656</td>
</tr>
<tr>
<td>Household size</td>
<td>6.18</td>
<td>8.11</td>
<td>7.14</td>
<td>-5.854***</td>
</tr>
<tr>
<td>Farm size (ha)</td>
<td>6.85</td>
<td>4.87</td>
<td>5.87</td>
<td>8.251***</td>
</tr>
<tr>
<td>Farming experience (years)</td>
<td>25.34</td>
<td>29.18</td>
<td>27.26</td>
<td>-5.770***</td>
</tr>
<tr>
<td>Level of education</td>
<td>2.48</td>
<td>2.50</td>
<td>2.49</td>
<td>-0.078</td>
</tr>
</tbody>
</table>

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The Propensity Score Matching Estimates

The results from the propensity score matching analysis are presented Table 5. The common support condition was imposed and the balancing property was set and satisfied in the entire estimated model at 5% level of significance. Table 5 shows that matching restricts the control sample (non-adopters) in order to increase the similarity of the subsample of non-adopters cases that are directly compared with the adopters’ cases, in order to estimate the consequences of adoption. Also the Table presents the balancing information for propensity scores for each covariate before and after matching. The standardized bias difference between adopters and non-adopters was used to quantify the bias between treatment and control samples. In almost all cases, it is evident that sample differences in the raw data (unmatched data) significantly exceed those in the samples of matched cases. The process of matching thus creates a high degree of covariate balance between the treatment and control samples that were used in the estimation procedure.

Table 5 shows that, before matching, several variables such as household size, social capital, farm size, farming experience and perceived economic benefit exhibit statistically significant differences, while after matching the covariates are balanced. This is consistent with a priori expectations. This result clearly shows that the matching procedure is able to balance the characteristics in the treated (adopters) and the matched comparison groups (non-adopters). The distribution of the covariates after matching and the pseudo-$R^2$ from logit estimation indicate a good matching quality for all these estimations. The distribution of the propensity scores and the region of common support are shown in Fig.1 and 2. These figures show the bias in the distribution of the propensity scores between the adopters and the non-adopters and serve to underline the general importance of proper matching as well as the imposition of the common support to avoid bad matches. The matching procedure was performed only in the region of common support. It was based on dropping observations from the adopter group whose p-score is higher than the maximum or less than the minimum p-score of the non-adopters (Leuven and Sianesi, 2003).

This result was therefore used to evaluate the effect of adoption of pest management innovation method on yield, income and poverty status among groups of cocoa farmers having similar observed characteristics.

Table 5 Indicators of Covariate Balancing, Before and after Matching

| Variable | Sample | Treated | Control | %bias | %|bias| reduction | Mean | t-test | T | p>||t| |
|----------|--------|---------|---------|-------|------|-------------|------|--------|---|-----|
| Income (₦) | 304,380 | 213,560 | 259,162 | 5,420*** | 8.053*** |
| Yield/ha | 40.07 | 28.12 | 34.10 | - | |

Source: Data analysis (2010).
*** means significant at 5% level.
4.3.1 Estimated Treatment Effect

The effect of adoption of pest management innovation method on yield, income level and measures of poverty status of adopting households were estimated through three different methods with replacement: the nearest neighbour, kernel based matching and radius caliper matching. The results of the three algorithms yielded qualitatively similar results. The results are presented in Tables 6 - 8. The overall matching estimates showed that adoption of pest management innovation method had a positive and robust effect on income, an indication of poverty reducing effect (Table 8). The causal effect of adoption of pest management innovation method is expected to increase the yield of adopting household by approximately 900 kg per cropping season (Table 6). This result suggests that much was lost to pest and disease in spite of using synthetic pesticides. However, adopting pest management
innovation method afforded the cocoa farmer opportunity to increase their yield (per hectare) which consequently impacted their income positively.

Furthermore, the causal effect of the indigenous method adoption on household’s income is positive and highly significant at 5% level. The value equals ₦70,685.332. The value is the average difference between incomes of similar pairs of households belonging to different adoption status. The result suggests that adopters of pest management innovation method earned ₦70,685.332 more than non-adopters. The matching procedure applied to the probability of the household to be poor indicated that adopters were less likely to be poor by about 13.6% points (Table 8). This is consistent with a priori expectations. As income of cocoa farmers increases due to the effect of adoption, poverty level is expected to reduce. In this case, a unit increase in income due to adoption of pest management innovation method would decrease adopters’ propensity to fall below the poverty line by 13.6 percent. This finding qualitatively agrees with Mendola, (2007) and is statistically significant at 5% level. The poverty incidence, depth and severity for the adopters were 22%, 8.1% and 1.4% respectively while for the non-adopters they were 29.3%, 11.3% and 2.9% respectively indicating that the adopters have comparatively lower poverty rate than non-adopters of pest management innovation (Table 8). This result answers the counterfactual question which would be of value in predicting the effects of adopting an alternative cocoa pest management method.

Table 6 Estimation of ATT: Effect of Adoption of Pest management innovation Method on yield/ha of Adopting Household.

<table>
<thead>
<tr>
<th></th>
<th>Nearest neighbor</th>
<th>Kernel matching</th>
<th>Radius caliper</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATT</td>
<td>900**</td>
<td>775.85**</td>
<td>916.95***</td>
</tr>
<tr>
<td>Standard error</td>
<td>8.479</td>
<td>7.124</td>
<td>3.734</td>
</tr>
<tr>
<td>Treated</td>
<td>67.574</td>
<td>67.574</td>
<td>67.574</td>
</tr>
<tr>
<td>Control</td>
<td>49.559</td>
<td>52.057</td>
<td>49.234</td>
</tr>
</tbody>
</table>

**, *** indicate significant at 5% and 1% respectively.

Source: Data analysis, 2010.

Table 7 Estimation of ATT: Effect of Adoption of Pest management innovation Method on Income of Adopting Household.

<table>
<thead>
<tr>
<th></th>
<th>Nearest neighbor</th>
<th>Kernel matching</th>
<th>Radius caliper</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATT</td>
<td>82,761.764**</td>
<td>70,685.332**</td>
<td>70,931.498***</td>
</tr>
<tr>
<td>Standard error</td>
<td>108,180.591</td>
<td>34,568.988</td>
<td>17,829.043</td>
</tr>
<tr>
<td>Treated</td>
<td>41108.625</td>
<td>297,629.412</td>
<td>285609.160</td>
</tr>
<tr>
<td>Control</td>
<td>214,867.647</td>
<td>266,944.079</td>
<td>214677.662</td>
</tr>
</tbody>
</table>

**, *** indicate significant at 5% and 1% respectively.

Source: data analysis, 2010.
Table 8: Estimation of ATT: Effect of Adoption of Pest management innovation Method on Poverty of Adopting Household

<table>
<thead>
<tr>
<th>Outcome</th>
<th>ATT</th>
<th>Standard error</th>
<th>Treated</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH Poverty *</td>
<td>-0.137**</td>
<td>0.069</td>
<td>0.209</td>
<td>0.347</td>
</tr>
</tbody>
</table>

**, significant at 5%  
*, household poverty was measured as dummy  
Source: Data Analysis, 2010

Table 6: Poverty incidence depth and severity by adoption status

<table>
<thead>
<tr>
<th>Poverty Indices</th>
<th>Headcount</th>
<th>Depth</th>
<th>Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adopters (%)</td>
<td>21.6</td>
<td>8.1</td>
<td>1.4</td>
</tr>
<tr>
<td>Non adopters (%)</td>
<td>29.3</td>
<td>11.3</td>
<td>2.9</td>
</tr>
</tbody>
</table>

Source: Data Analysis, 2010

Conclusion

The adoption of Siam Weed Soap Solution to manage the pest and disease of cocoa has the potential to increase yield, income and consequently reduce the propensity of resource poor farmers to fall below the poverty line. The adoption was found to have increased the yield of the cocoa farmers, improve their income status and reduce their poverty rates. These results suggest that the development of Siam Weed Soap Solution is critical to improve the yield and income of resource poor cocoa farmers in the tropical cocoa producing areas.

Since poverty is widespread and is largely rural, and several projects designed to tackle poverty menace has not yielded desirable result, the finding from this study suggests the need to consider farmers’ productive capacity, their immediate environment and direct development or redesign of their local agricultural resource technology are critical in improving their well-being and increasing returns to resource-poor farmers. A closer look at the implication of the findings from this study reveals that poverty in the rural areas are rarely due to insufficient production but rather to poor health of farmers, disregard for indigenous knowledge and local agricultural resource management.

Findings from this study also suggest there is a lot of hope that botanical pesticides will take us a long way in fighting the dangers associated with conventional pesticides especially in rural based communities. This justifies the need to research into the effect of the indigenous technology adoption on income of farmers. While highlighting the relevance of methodological issues in assessing causal relationships, the analysis showed the potential role of local technologies in improving farmers’ food output and reducing poverty through the enhancement of farmers’ productive capacity.

Policy implications of this study for the lawmakers include the need to enact law that protect local resource because of inherent potential in them if well harnessed. Indigenous communities are also encouraged to maintain their practices while embracing civilizations. However, the indigenous method
capacity for a large scale development beyond the host community remains in doubt. Future researchers on this study are encouraged to look into the multiplicative potential of botanicals in managing pests and diseases of crops.

Fig. 1: Graph of propensity score for adopters and non-adopters
Source: Data analysis, 2010

Fig. 2: Graph showing propensity score distribution and common support for propensity score estimation
Source: Data analysis, 2010

References


Sosan, M.B., Akingbohungbe, A.E., Durosinmi, M.A., and Ojo. 2010. Erythrocyte Cholinesterase Enzyme Activity and Haemoglobin Valves in Cacao Farmers of
