Impact of the adoption of semi-mechanized technologies of shea processing on rural women’s income in Northern Benin (West Africa)

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In Benin, the shea sector is one of the most promoted sectors in government’s attempt to diversify sources of farm income. The objective of this study is to evaluate the impact of the adoption of the semi-mechanized shea processing on the income of rural women in northern Benin. In total, a random sample of 200 women processing shea was investigated. A probit model was firstly run to analyze the factors determining the adoption of the semi-mechanization. Then, a multiple regression model was used to assess the impact of adoption on women’s income. The results highlighted that, the adoption of semi-mechanization was determined by availability of electricity, availability of a market, contact with extension services and shea processing as main activity for woman. Moreover, the adoption of semi-mechanization has induced a positive and significant increase of rural women’s income up to 103 914 Francs CFA. As a result, it is important that agricultural policy reinforce the promotion of modern agricultural processing technologies to improve the added value and to reduce poverty in rural areas. As well, electricity and market access, women’s level of education and contact with extension need to be improved.

Key words: Adoption, impact, shea processing, semi-mechanization, income, Benin.

INTRODUCTION

In Benin, cotton is the main cash crop which contributes over 75% to the export earnings (DSCRCP, 2007). The crisis in the sector has made the Government to promote new export sectors such as shea processing. Traditionally, the nuts mainly transformed in shea butter are manually crushed in mortar and then ground to stone. This laborious work is very difficult and requires a high amount of man-power. However, following the diagnostic survey of the processing of food products in Benin, the mechanization of certain stages of shea processing...
(semi-mechanization) has been identified as priority need that can reduce drudgery in the sector (Kruit and Godjo, 1998). As well, Ahouansou and Singbo (2005) showed that, in shea processing, grinding and milling operations are most restrictive. In addition to these operations, women’s exposure to heat and smoke for hours during the roasting process and low yield (10 kg of roasted product per and per person on average) are constraints weighing down on shea processing in Benin (Yabi et al., 2009).

For improving the processing conditions, several tools are developed by manufacturers among which stand the Benin Cooperative of Agricultural Equipment (COBEMAB1). Through the Agricultural Program and Food Technology (PTAA2), the National Agricultural research System (INRAB3) supports this initiative, and from 2002 to 2003, an adaptation test of motorized equipment was conducted by the Program in the areas of N’Dali, Banikoara, Djougou, and Natitingou. The results showed that, the complex equipment made up a mill of BCAE and a corn mill motor is effective in enabling women processing shea to save up to 75% of their initial working time (Singbo and Ahouansou, 2005).

Nowadays in Benin, equipment such as the grinder or crusher, the shea grinder, the complex made up grinder and shea mill, and the churn are introduced and made available for women processing shea. Despite their performance in terms of saving time, it is relevant to check out whether the introduction of these technologies for semi-mechanized shea processing has increased the income of rural women, contributing to reduce rural poverty. Moreover, since the introduction of these technologies in shea parks of northern Benin, evaluation studies of their economic impact on adopting women have not been conducted yet. Thus, this study aims at assessing the impact of the semi-mechanization of shea processing on the income of rural women in shea parks in northern Benin.

Theoretical background

Talking about impact assessment, the major problem is to isolate the effects of a project, a program or an innovation on the target group. To deal with this problem, several frameworks or approaches are available. The common ones are the “before-after” approach, the “with-without” approach, the so-called “naïve” approach, the experimental approach, and the non-experimental approach (Yabi, 2008). The ‘before-after’ approach compares the performance of key variables after the introduction of technology with the one before its introduction. But this comparison of situations “before” and “after” the introduction of a given innovation does not isolate the effects related to exogenous factors (inflation, rainfall, natural disasters, economic and agricultural policies for instance) that may arise during the adoption process and that could determine the adoption rate as well as the impact on individual. Moreover, this approach imposes a baseline study before the introduction.

Otherwise, data of the conditions “before” are not available.

In comparison with the "before and after" approach, the "with-without" one seems clearer an easier (Scherr and Muller, 1991). It divides the potential target group into two subgroups. One subgroup has received the technology (beneficiary or treatment group) and the other which has not (non beneficiary or control group). In this approach, one compares the two subgroups. The problem while using this approach is to find out respondents that are similar enough so that only the adoption or not of the technology sets out the difference between them.

The “naïve” approach consists in taking a random sample of adopters and non-adopters of a given technology and using the simple difference in mean scores observed in both groups as the impact estimation. While this estimation method is commonly used in the literature (Adekambi, 2005), the estimator is potentially biased (Heckman, 1990; Diagne, 2003) and does not take into account the socio-economic characteristics of operators. The experimental approach consists in setting up a group of people having the same rights and agreeing to participate in the experiment. The selected people are randomly divided within two subgroups: one group of those who receive the intervention (treatment group) and the second group of those who do not receive (control group). Participants in this experiment are randomly selected and any difference with non-participants is only due to treatment. This experimental approach is considered to be the most reliable (unbiased estimates) and gives results easier to interpret (Cochrane and Rubin, 1973; Bassi, 1984). However, this type of evaluation is difficult to apply in practice because of ethical problems arising in the case of social phenomena (Diagne, 2003). In addition people adopting are likely to be willing to participate in the experiment and one might come up with zero non-adopters.

Economists widely use non-experimental approach based on economic theory and econometric analysis to guide and minimize potential errors in the impact estimation (Diagne, 2003). Non-experimental approaches are used when it is not possible to select a control group. In this framework, it is possible to compare program participants with non-participants by using statistical methods to control the observed differences between the two groups that could influence the impact indicator regardless to the program participation. Indeed, it is possible, using regression analysis, to obtain a "control" of age, income, gender and other characteristics of the participants. This assessment approach is relatively inexpensive and easy to apply, but the results interpretation is not straightforward and the results

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they themselves may be less reliable (Diagne, 2003), if the researcher was not aware of econometrics methods.

In this study, we consider three main technologies aiming at semi-mechanized shea processing and introduced in northern Benin: the grinder, the shea mill, and the entire complex (grinder + mill). Since the technologies under consideration are already introduced, we apply an ex-post evaluation. Regarding the strengths and weaknesses of the different impact assessment frameworks, we used a non-experimental approach. This approach is based upon principles of the “with-without” approach improved with econometrics methods. Finally, following the problem statement of this study, we mainly focus on income as impact estimator.

MATERIALS AND METHODS

Study area and database

The study area includes the 3 shea parks (Parakou, Bembèreke, and Kandi) in northern Benin situated between 09° 20’ and 12° 30’ North latitude and 0° 45’ and 3° 20’ East longitude. Thus, it is located in a Savannah area with a Sudano-Guinean climate characterized by a wet season (mid April to late October to early November). The annual rainfall varies between 900 and 1200 mm. This climate is very suitable to the shea production, making the study environment an area of high production and consumption of shea butter in Benin.

In the study area, 20 villages well known in shea production and processing were selected with the support of agricultural extension officers. The respondents were women performing activities related to shea processing. The sampling was conducted randomly (based upon a list of women processing shea per village) and included an initial number of 200 women producers of shea butter (10 per village). Regarding the assessment approach adopted, the sampled women were set into two subgroups: one group using at least one of the three main technologies of semi-mechanization and the second control group using the traditional method for shea processing.

Primary quantitative and qualitative data such as women’s characteristics, technologies adopted and the production of shea butter were collected through a survey method by using an individual questionnaire. As well, the triangulation of data was done through semi-structured interviews, focus group discussions and interviews with key informants.

Modeling the impact of adoption on income

We aim at determining the effect of technological change on an outcome indicator defined by y (income). Let us call y as the income level for an individual i if he uses the new technology and y as the level if he does not use the new technology. Then, we consider Wi as a binary variable taking the value 1 when the technology is adopted and 0, if not. The causal effect of technology adoption for that individual i is the difference between y and y:

\[ \Delta y = y_1 - y_0 \]  

(1)

The main problem while estimating \( \Delta y \) is that, for a given individual, the income is observed either following the adoption or before the adoption, but never both at once. Then, let us quote by P the probability of technology adoption. Having this, \( \Delta y \) is due to a change \( \Delta P \). Thus we might consider that:

\[ \Delta y / \Delta P = \beta \]  

(2)

By moving to an infinitesimal change (d instead of \( \Delta \)), we come up with:

\[ dy / dP = \beta \]  

(3)

From equation [3], y can be expressed as a function of P and other factors Z. It comes out that:

\[ y = F (P, Z, e) \]  

(4)

Where, Z stands for exogenous factors other than P and e for the error term assumed to have a normal distribution with mean 0 and constant standard deviation. Since P is by hypothesis determined by some characteristics C specific to the individual adopting the technology, we have:

\[ P = G (C, v) \]  

(5)

Where, C stands for exogenous factors (education level, gender, contact with a project officer for instance) determining the probability of adoption, and v for the error terms assumed to be normally distributed with average 0 and constant standard deviation.

With such specification, we come up with two models: the adoption model (Equation 4) and the impact model (Equation 5). Wooldridge (2002) suggests estimating initially, the adoption model. Then, in a second step, the model impact by integrating an estimated probability \( \hat{G} \) such as:

\[ y = F (\hat{G}, Z, e) \]  

(6)

In case the estimated coefficient of \( \hat{G} \) is significant, Rosenbaum and Rubin (1983) demonstrated that, we could identify an average causal effect of technological change within a population. Their idea is to pinpoint the difference between the average level of the indicator of beneficiaries and non beneficiaries of the technology. This gives the average treatment effect (ATE) which is defined by the difference between the estimated income \( \bar{y} \) when the estimated probability is 1 and the estimated income \( \bar{y} \) when the same probability is 0. Mathematically, we have:

\[ \text{ATE} = [(\bar{y}/P = 1) - (\bar{y}/P = 0)] \]  

(7)

This indicator which measures the impact of the technology on an individual selected at random from the population is also equal to the average impact of technology on the entire population (Heckman, 1997; Wooldridge, 2002). Empirically, the logit or probit models was based upon the Maximum Likelihood method are widely used for estimating the adoption model (Equation 5).

According to Heckman (1997), both logit and probit models do often generate similar results, and choosing one of them depends on the skill in data analysis. Thus, we used the probit model to estimate Equation 5. Thus, we get the following empirical equations:

\[ G = \alpha_0 + \alpha_1ELECT_i + \alpha_2EXPE_i + \alpha_3CONTVUL_i + \alpha_4MARCHE_i + \alpha_5ACTPBEUR_i + \alpha_6EDUCFT_i + v_i \]  

(8)

and

\[ y_i = \beta_0 + \beta_1\hat{G}_i + \beta_2\hat{EVT}_i + \beta_3AUTREVi + \beta_4EXPE_i + \beta_5ACTPBEUR_i + \beta_6LDMARCHE_i + \beta_7EDUCFT_i + \beta_8ABLEFTH_i + \beta_9ABAUTREVi + \beta_{10}\text{ABLDMARCHE}_i + \epsilon_i \]  

(9)
Where, $G$ stands for the distribution function of technology adoption and $\hat{G}$, for its value estimated from Equation 8. Similarly, $\gamma_i$ is the net annual income coming from shea processing of the $i^{th}$ woman. This income is obtained by subtracting from the total revenues the total costs related to processing. The coefficients $\alpha$ and $\beta$ were estimated by using the Maximum Likelihoods (ML) and ordinary least squares (OLS) methods respectively.

**Exogenous variables and hypotheses to be tested**

The selection of the prospective exogenous or explanatory variables was grounded in the literature and in our field observations:

a) Availability of electricity in a village (ELECT): Most of the new processing technologies use electric power. Therefore, the availability of electricity in the village is a prerequisite for adoption of these new technologies.

b) Years of experience in shea processing (EXPE): Following Huffman (1977) and Kokoye et al. (2013), learning from experience reduces allocative errors. Thus, we hypothesize that women having long experience of the traditional way of shea processing will be less likely to adopt new technologies.

c) Contact with extension (CONTVUL): According to Maddison (2006), people enjoying free extension advice are likely to adapt. In this line, we expect a positive correlation between the contact with extension and the adoption of new processing technologies.

d) Availability of market in the village (MARKET): The shea processing is a market oriented activity in northern Benin. Thus, the market access is an incentive for women processing shea. Stating this, we hypothesize that the market availability is positively correlated with the adoption of new technologies.

e) Shea processing as main activity of the respondent (ACTPBEUR): We assume that women invest more time and money in their main activity. Therefore, we expect a positive correlation between having shea processing as main activity and adoption of new processing technologies.

f) The respondent’s formal education status (EDUCF): Educated farmers are more likely to respond to environmental changes by adapting (Maddison, 2006). They might also be likely to understand easily the advantage of new processing technologies (time saving and health benefits for instance). Therefore, the education level is expected to have a positive effect on the adoption of technologies.

g) Quantity of family labor available for processing (LEFTHJ): Here we make the assumption that when the family labor is available women are less willing to invest in new technologies. Then the quantity of family labor available for processing is expected to have a negative impact on the adoption processing of new technologies.

h) Income from other activities of women (AUTREV): The availability of income sources can make women able to afford investments related to new technologies use. Thus, we expect a positive correlation between income from other activities and adoption of new processing technologies.

Interaction between adoption and amount of family labor available (ABLEFTHJ), interaction between adoption and income from other activities (ABAUTREV) and interaction between adoption and distance from the village to the nearest market (ABLDMARCHE) were defined to measure the impact of the interaction between the adoption of semi-mechanized shea processing and amount of family labor available (LEFTHJ), income from other activities (AUTREV), and distance from the village to the nearest market (LDMARCHE) respectively. They enable to isolate composite impacts on the income of women adopting the new technologies. These variables were obtained by multiplying the estimated probability $\hat{G}$, by the three variables LEFTHJ, AUTREV and LDMARCHE respectively. EXPE, ACTPBEUR, and EDUCFT are assumed to determine indirectly women’s income. Therefore, they are introduced in both adoption and impact models.

**RESULTS**

**Women’s characteristics**

Descriptive statistics of women’s characteristics are presented in Table 1. These results indicate that, 56% of the respondents adopt new shea processing technologies. Women have a consistent experience in shea processing (median 15 years), but few (23%) of them have contact with extension services. The level of education very low (5%).

**Estimation of the adoption probability**

The results of the adoption model indicate that, the model is highly significant at 1% (Table 2). The coefficients of all explanatory variables, except the years of experience, positively influence the adoption of the semi-mechanized shea processing. Electricity availability, contact with extension, and market availability are significant at 1%
Table 2. Results of econometric estimation of the adoption model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients</th>
<th>Standard error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability of electricity in the village</td>
<td>1.250 ***</td>
<td>0.2082</td>
<td>0.000</td>
</tr>
<tr>
<td>Experience in shea processing</td>
<td>-0.124</td>
<td>0.119</td>
<td>0.299</td>
</tr>
<tr>
<td>Contact with extension</td>
<td>0.858***</td>
<td>0.276</td>
<td>0.002</td>
</tr>
<tr>
<td>Availability of market in the village</td>
<td>0.771 ***</td>
<td>0.212</td>
<td>0.000</td>
</tr>
<tr>
<td>Shea processing as main activity</td>
<td>0.622**</td>
<td>0.248</td>
<td>0.012</td>
</tr>
<tr>
<td>Respondent received a formal education</td>
<td>0.090</td>
<td>0.511</td>
<td>0.860</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.072 ***</td>
<td>0.366</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Dependent variable: Adoption probability (G)
Log pseudo-likelihood = -101.086
Wald $\chi^2$ (6) = 58.54***
Number of observations = 192

Note: *** and **: Significant at 1 and 5%, respectively. Source: Authors’ estimations.

while having shea processing as main activity is significant at 5%. The formal education status is not significant in the model. Subsequently, the determinants of the adoption of at least one type of technology are the availability of electricity or market in the locality, the contact with extension services, and the shea processing as main economic activity.

As expected, although the coefficient of the years of experience in processing is not significant, the more women are experienced, the more they are more likely to use traditional methods for shea processing. The level of formal education should have a significant positive impact on adoption, but the small proportion of women who received this education (5%) made its impact positive but not significant.

Impact of adoption on the income of women

To estimate the impact of adoption on women’s income, other variables were used in addition to the estimated probability of adoption as described in the empirical model. The descriptive statistics of these variables are presented in Table 3. On average, women interviewed did earn 173,218 Francs CFA as income from shea processing. Women adopting processing technologies have higher incomes than they fellow women who did not adopt. This difference in incomes that could come from the difference in technology between the two groups will be tested by the impact model.

Women who are not adopting travel a longer distance (0.899 km) than the ones adopting (0.478 km) in order to access market. This result could be explained by the fact that, most of women adopting processing technologies belong to village-groups and deal their products in group to traders who use to collect the butter in the village. The amount of available man-power within the household, the income from other activities, the experience in processing and the formal education status are more or less the same between women adopting and they fellow who did not adopt. Finally, a high proportion of women adopting the processing technology (90%) have shea processing as their main economic activity.

Table 4 presents the econometric results of the impact model. The Fisher F statistic indicates that, the model is highly significant at 1%. The over-identification test of Hansen used to test the independence between the instruments and the error term is not significant ($p = 0.110$). The significance of the interaction terms was tested by the Wald test. The value of this test is 74.29, and is significant at 1%. Thus, the null hypothesis which states that, all interaction terms are zero cannot be accepted.

The coefficient of the adoption probability $G$ estimated from the adoption model is positive and significant at 1%. Therefore, there is a positive correlation between income and adoption. Put into a simplistic way, adopting the new shea processing technologies ensure an increase of the annual income. Furthermore, the average impact of the adoption of the semi mechanization of shea processing on the annual income of women is 103,914.1 Francs CFA/year.

In addition to the adoption, the family labor available, the shea processing as main activity and the income from other activities have positive and significant coefficients at 1 and 5%, respectively on the women income generated by shea processing. Indeed, women processing shea and having many children, so more workers, have higher incomes. The shea processing as main activity is the key to improving income. This result is not surprising because women having shea butter processing as main activity spend most of their time in doing the activity. Finally, revenue from other activities did promote capital accumulation for a better investment in shea processing. As a result, these revenues have a positive impact on income.

Considering the interactions between adoption and the three target variables, it comes out that, revenues from
Table 3. Descriptive statistics of explanatory variables used in the impact model.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Adopting</th>
<th>Not adopting</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quantitative: Means (Standard deviation)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual income from shea processing</td>
<td>225 175 (30 002)</td>
<td>121 261 (52 100)</td>
<td>173 218 (60 121)</td>
</tr>
<tr>
<td>Estimated probability of adoption</td>
<td>0.96 (0.14)</td>
<td>0.00</td>
<td>0.57 (0.14)</td>
</tr>
<tr>
<td>Amount of family labor available</td>
<td>4.903 (0.758)</td>
<td>4.972 (0.828)</td>
<td>4.93 (1.12)</td>
</tr>
<tr>
<td>Income from other activities</td>
<td>117218 (94008)</td>
<td>101421 (54653)</td>
<td>109 319 (108 740)</td>
</tr>
<tr>
<td>Experience in processing</td>
<td>2.473 (0.830)</td>
<td>2.339 (0.864)</td>
<td>2.41 (1.20)</td>
</tr>
<tr>
<td>Distance from the village to nearest market</td>
<td>0.478 (0.708)</td>
<td>0.899 (0.950)</td>
<td>0.690 (1.18)</td>
</tr>
<tr>
<td>Interaction between adoption and amount of family labor available</td>
<td>-0.030 (0.758)</td>
<td>0.00</td>
<td>-0.030 (0.758)</td>
</tr>
<tr>
<td>Interaction between adoption and income from other activities</td>
<td>6993.69 (94008.3)</td>
<td>0.00</td>
<td>6993.69 (94008.3)</td>
</tr>
<tr>
<td>Interaction between adoption and distance from the village to the nearest market</td>
<td>-0.186 (0.708)</td>
<td>0.00</td>
<td>-0.186 (0.708)</td>
</tr>
<tr>
<td><strong>Qualitative: Relative frequencies (%)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shea processing as main activity</td>
<td>90.4</td>
<td>57.6</td>
<td>74.0</td>
</tr>
<tr>
<td>Formal education</td>
<td>94.2</td>
<td>96.4</td>
<td>95.3</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.

Table 4. Results of the impact model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients</th>
<th>Standard Error</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-331096.3**</td>
<td>151548.8</td>
<td>0.029</td>
</tr>
<tr>
<td>Estimated probability of adoption</td>
<td>103,914.1***</td>
<td>33,517.14</td>
<td>0.002</td>
</tr>
<tr>
<td>Amount of family labor available</td>
<td>121118.3***</td>
<td>26406.15</td>
<td>0.000</td>
</tr>
<tr>
<td>Revenues from other activities</td>
<td>0.862**</td>
<td>0.388</td>
<td>0.026</td>
</tr>
<tr>
<td>Experience in shea processing</td>
<td>-13481.9</td>
<td>10116.4</td>
<td>0.183</td>
</tr>
<tr>
<td>Shea processing as main activity</td>
<td>87,007.48***</td>
<td>24020.91</td>
<td>0.000</td>
</tr>
<tr>
<td>Distance between village and nearest market</td>
<td>-29,876.21</td>
<td>22,102.64</td>
<td>0.176</td>
</tr>
<tr>
<td>Formal education status</td>
<td>33563.45</td>
<td>46969.87</td>
<td>0.475</td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between adoption and amount of family labor available</td>
<td>-115777.3**</td>
<td>52033.01</td>
<td>0.026</td>
</tr>
<tr>
<td>Between adoption and revenue from other activities</td>
<td>4.520474***</td>
<td>0.585</td>
<td>0.000</td>
</tr>
<tr>
<td>Between adoption and distance from the nearest market</td>
<td>84192.76**</td>
<td>43031.93</td>
<td>0.050</td>
</tr>
<tr>
<td>Average treatment effect (ATE)</td>
<td>103914.1***</td>
<td>37031.38</td>
<td>0.006</td>
</tr>
<tr>
<td>Dependent variable</td>
<td>Revenue of shea processing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald test (H0: all interaction terms = 0)</td>
<td>$\chi^2 (3) = 74.29 , (p = 0.000)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fisher F statistic</td>
<td>$F = 53.14; , df1 = 11; , df2 = 180$ and $p = 0.000$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>192</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *** and **: Significant at 1 and 5%, respectively. Source: Authors’ estimations.

other activities and the distance from the nearest market have a positive impact on income generated by the processing activity. However, the interaction between adoption and amount of labor has a negative impact on the income of women adopting new technologies. As we hypothesize, this is simply due to the fact that women
having higher labor available are already less willing to adopt new technologies of processing.

**DISCUSSION**

Three factors are identified as determinants of the adoption of semi-mechanized processing of shea nuts. It is about the availability of electricity or market in the locality, the contact with extension services and the shea processing as main activity for women. These finding confirm the theoretical hypotheses of the study. As well, several authors highlighted the key role of variables such as extension services in the adoption of new technologies (Bravo-Ureta et al. 2005; Glélè et al. 2008).

By adopting the technologies of shea processing, the results pinpointed that women could improve their incomes. This supports the general hypothesis stating that adoption of agricultural innovations lead to improvement of incomes. Glélè et al. (2008) found out that, adopters of improved cassava varieties derive more income per hectare than non-adopters and they earn on average 140,358 Francs CFA per hectare against 46,984 Francs CFA per hectare for their fellow non-adopters. Similar studies were also conducted in other African countries and the results are consistent with those found out in Benin.

According to Benin et al. (2011), the technologies adopted by farmers in Uganda, through the National Program for agricultural extension services, have a positive impact on incomes. The direct and indirect impacts of adopters are estimated between 37 and 95% higher in comparison with non-adopters. Benin et al. (2011) also reported that, this positive impact increases over time. For instance, between 2004 and 2007, it increased from 27% to 55% per capita. In the same vein, Kato et al. (2011) showed that in the Nile Basin in Ethiopia, technologies for soil and water conservation have a positive impact on agricultural output. Because the performance of agriculture determines the level of income, these technologies have a positive impact on income.

According to Hassan and Thurlow (2010), the water management strategy adopted by the South African producers had an impact, an improved domestic production by 0.4% annually from 1994 to 2007; implicitly improving producers’ income over the same period. Bellemare (2010) found out in Madagascar that, the adoption of technologies promoted by extension agents improves productivity and results indicated that, the elasticity of performance in relation with the number of visits is between 1.3 and 1.7. In Kenya, the adoption of technologies (such as systems of rotation with green fertilizers) of the International Center for the Improvement of Maize and Wheat Improvement Center (ICIMWIC) allowed producers to improve their yields (De Groote et al., 2010). But, as several authors emphasized, the adoption of new technology can have a positive impact if the additional costs are offset by the additional production. As proof of this, LUCOP-TAN (2010) found out that the adoption of new technologies for the development of the valleys in the region of Tahoua in Niger had no impact on producers’ income. Indeed, the costs associated with the development of the valleys are very high and the additional production value obtained does not cover the aforesaid costs.

Subsequently, the impact of adopting a new agricultural technology supports the economic theory of the producer’s balance. The adoption becomes economically profitable from when the marginal revenue generated equal the marginal costs. In this case, the economic impact of the technology adoption is positive.

**Conclusion**

This study analyzed the impact of the adoption of semi-mechanized shea processing on income of rural women in northern Benin. The findings highlighted that, the adoption of shea processing technologies increases women’s incomes. As policy implication, it is important to strengthen the promotion of new technologies in order to boost the agricultural development in general and the shea processing in particular. In this line, special emphasis should be put on modern technologies of processing agricultural products to create more value added, implying more wealth.

Moreover, electricity and market access, women’s level of education and contact with extension need to be improved. This study focuses only on income. Future researches could address other variables such as education level of children and health.

**Conflict of Interests**

The author(s) have not declared any conflict of interests.

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