Impact of use of credit in rice farming on rice productivity and income in Benin

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Abstract

This paper aims to assess the impact of the use of credit in rice farming on productivity and income in Benin. It applies the potential outcomes framework to data collected from 342 rice farmers in Benin to estimate the Local Average Treatment Effect (LATE). The findings show that the use of credit in rice farming has a positive and significant impact on farmers' rice yield, rice output, rice income, per capita rice income, annual household income and per capita annual household income. Access to credit allowed users of credit in rice farming to improve their inputs utilization (rice land, fertilizer and labor) in order to increase not only their yields and rice output, but also their rice income and their households' annual income. Therefore, facilitating access of rice farmers to agricultural credit is a good strategy for supporting rice sector development, and therefore contributing to food security and poverty alleviation in Benin. However, the impact was not homogeneous among farmers in the population. For all the impact indicators (yield, output, rice income and annual household income), the impact was higher for female potential users of credit than their male counterparts. Therefore, it is important to control for heterogeneity in impact assessment studies in order to appreciate the real effect of interventions on different social categories in the target population for targeted actions.

Keywords*: Rice, Credit, Gender, Impact, Income, Productivity, Benin, Local Average Treatment Effect*

1. Introduction

Agriculture is the mainstay of most developing countries' economies. On average, the sector accounts for 70% of full-time employment, 33% of national income, and 40% of total export earnings in Africa (Otsuka *et al*., 2013). Therefore, increasing agricultural productivity, especially in countries facing land constraints, requires the intensification of farming systems through yield-enhancing technologies and strategies (Borlaug, 2001; Diao *et al*., 2007). Rice is the most strategic food crop in West Africa because of its contribution to food security of the populations and its impact on the economy of households and countries (Seck et al., 2013; FAO, 2013). In response to the 2008 food crisis, Benin, like several other African countries, developed policies and programs to boost agricultural production through the intensification of farming systems with particular emphasis on rice sector development (Republic of Benin, 2011; 2007; MAEP, 2010). One of the major orientations of these programs is the development of thirteen promising sectors including rice. The objective is to produce 385 000 tons of milled rice by 2015. In addition, with the support of the African Coalition for Rice Development (CARD), Benin developed its National Rice Development Strategy (NRDS) in 2010 (MAEP, 2011). In all these rice sector development programs, one of the key strategies for rice production intensification is to improve access of small rice farmers to suitable and timely credit.

Indeed, it is generally recognized that credit plays a crucial role in economic development in general and agricultural development in particular (Diagne and Zeller, 2001; Diagne, 2002; Honlonkou *et al*., 2005; Simtowe and Phiri, 2007; Fall, 2008; Simtowe *et al*., 2008; CTB, 2012). Therefore, credit appears as a solution to the weakness of rural savings by allowing producers to cover the expenses related to production. According to Diagne (2002), the continuing inadequate and limited access of African farmers to credit is believed to have significant negative consequences for various aggregate and household-level outcomes, including technology adoption, agricultural productivity, food security, nutrition, health, and overall household welfare. In Benin, access to agricultural credit is one of the major constraints that limit agricultural development. According to Deveze (2000), credit constraint is very crucial in the African agricultural sector because of weather and land constraints, but also the unstable socio- economic environment. Other studies have shown that most the Microfinance Institutions (MFI) exclude farmers whose Internal Rate of Return (IRR) is lower than the cost of the loan, which is high in Africa. This limits farmers' productivity and therefore affects their income and livelihood. Indeed, the intensification of rice production requires a higher use of inputs (seed, fertilizers, labor, pesticides), especially in rainfed rice farming. In addition, the adoption of new technologies, which may require investment, is one of the key options for increasing rice productivity. Furthermore, as a result of recent financial, economic and food crises, input costs, including labor have drastically increased. In this situation, increasing rice production for self-sufficiency in Benin requires significant financial resources for farmers whose savings are generally low. Thus, additional suitable and timely financial resources need to be provided to farmers to enable them to cope with the high cost of inputs. Therefore, the issue of access to credit is essential for the development of rice farming in Benin. Access to credit is expected to have a positive effect on the adoption of new technologies, use of good and recommended agricultural practices and, therefore, on the productivity and farmers' livelihood. According to Diagne (1999), without a well-functioning financial market, there is unlikely to be a significant improvement in agricultural productivity and the livelihood of African rural populations. Furthermore, access to credit and its use in rice farming may significantly improve the demand for and use of suitable inputs (Fall, 2008). Thus, farmers who have access to credit and use it in rice farming could easily manage to get fertilizers, pesticides, labor and other inputs in required quantity and in a timely manner, especially when the credit is obtained before the cropping season. This would improve their productivity and income (Morduch, 1998; Robinson, 2001; Kodjo *et al.*, 2003; Honlonkou *et al*., 2005).

Like many developing countries, several initiatives have been taken and implemented by Benin's government and its partners to facilitate access to rural and poor populations, including rice farmers. These initiatives include the National Fund for Agricultural Development (FNDA), the Municipal Development Support Fund (FADEC), the Emergency Program for Food Security Support (PUASA), the credit component of the National Company for Agricultural Promotion (SONAPRA), the National Fund for Promotion of Enterprise and Youth Employment (FNPEEJ), the National Fund of Microfinance (FNM) and the Program of Micro-Credit for Poorest (MCPP). These initiatives have been undertaken and implemented by the government and aim to provide credit to vulnerable development actors including farmers and agricultural entrepreneurs. In addition to these governmental initiatives, rice farmers get agricultural credit from local and private initiatives such as the Local Banks of Agricultural Credit and Mutual (CLCAM), the Rural Banks for Savings and Loan (CREP), and various NGO and rural development projects. According to OCS (2010), the implementation of these initiatives has improved the access of farmers to agricultural credit, but the rate is still low. However, the real impact of the use of credit in agriculture is not well investigated.

This paper focuses on rice farming households and aims to assess the impact of the use of credit in rice farming on productivity and income. We assume that the use of credit in rice farming will improve the use of inputs by farmers, and enhance their productivity and income. The paper will also test the assumption that any technological change in agricultural systems affects men and women differently.

2. Methodology

2.1. The theoretical framework of impact assessment

The assessment of the impact of the use of credit in rice farming on productivity and income is based on the Sustainable Livelihood Framework (SLF) developed by DFID and its collaborators (Solesbury, 2003; DFID, 2001). It is an evolved thinking about poverty reduction and environmental management which deals with the way the poor and vulnerable live their lives and the importance of structural and institutional issues. The approach suggests development activities that are people-centered, responsive and participatory, multilevel, conducted in partnership with both the public and private sectors, dynamic and sustainable. It draws on the main factors that affect poor people's livelihoods and the typical relationships between these factors. The framework recognizes that every household and community has resources on which to build and support both individuals and the community in acquiring assets needed for their long-term well-being. It is quite attractive in the sense that it provides a simple but well-developed way of thinking about a complex issue (welfare). It is also attractive because it can be applied at various levels of detail as a broad conceptual framework or as a practical tool for designing programs and evaluation strategies.

As in every society, individual households in Benin are endowed with human capital (household members' skills, aptitudes, knowledge, etc.), natural capital (the quality and quantity of natural resources available like land, water, etc.), physical capital (infrastructure (roads, electricity, markets, etc., tools, and equipment used for increasing productivity), social capital (networks for cooperation, mutual trust, and support, etc.) and financial capital (savings and regular inflows of money including credit), which constitute the resource constraint based on which they maximize their well-being. These resources are affected by exogenous factors such as agro-climatic conditions (drought, rainfall, etc.), insect pests and diseases which hinder their productivity. Change in financial capital wrought through the availability of and access to credit for investment in rice production affect the rice farmers' perception, beliefs, expectations and preference toward different inputs used in production. This is because, based on the characteristics of the availability of credit and the possibility to get credit, farmers believe that using credit to improve their inputs use would increase their yield and they therefore anticipate strong benefits. This constitutes the farmers' 'value formation' that in turn will condition their decisions in terms of investment, crop and varietal choices, and resource allocation to various inputs. Their decisions have to change because the use of credit in rice production may need more land and different types of other inputs. This can be expected to affect their consumption, marketing of harvested quantities of different crop varieties, savings and income generation activities. Therefore, household decisions and choice constitute the farmers' behavioral outcomes, which will finally affect their productivity, income and poverty levels (livelihood outcomes). In this paper we investigate whether using credit in rice production enhances farmers' productivity and improves their incomes.

2.2. The analytical framework of impact assessment

In the growing literature on impact assessment of programs or policy interventions, many of the studies have usually relied on fairly macro approaches (Evenson and Gollin, 2003). On the other hand, many other micro-level studies have assessed the impact of the use of credit by simply examining the differences in mean outcomes of users and non-users, or by using simple regression procedures that include the use of credit status variable among the set of explanatory variables. Critics have pointed out that such simple procedures are flawed because they fail to deal appropriately with the self-selection bias caused by selection on observables or unobservables present in observational data collected through household surveys. For that reason, these studies fail to identify the causal effect of using new products from programs or policy interventions (Imbens and Wooldridge, 2009; Heckman and Vytlacil, 2005; Lee, 2005; Imbens, 2004; Rosenbaum, 2002; Heckman and Robb, 1985; Rosenbaum and Rubin, 1983; Rubin, 1974).

The potential outcome framework is increasingly becoming the standard approach to dealing with the self-selection bias issue for assessing the impact of programs or policy interventions (Rubin, 1974; Imbens and Wooldridge, 2009). The framework is also being advocated as a more suitable and rigorous framework for assessing the impact of endogenous treatment variables like the use of credit than the so called "economic surplus" method, which has been, until recently, the *de facto* standard method used by agricultural economists (De Janvry et al., 2010). The potential outcome framework is used to assess the impact of the use of credit on rice farmers' productivity and incomes.

Under the potential outcomes framework, each population unit with an observed outcome *y* has *ex-ante* two potential outcomes: an outcome when receiving a treatment and an outcome when not receiving a treatment. Here the treatment is use of credit in rice production *j*. Let D_j be the binary variable indicating the use of credit in rice production *j* with $D_j = 1$ indicating use of credit (i.e. $d_j = d_j^1$) and $D_j = 0$ indicating non-use of credit by a population unit (i.e. $d_j = 0$). Also, let $y_1 \equiv g(d_j^1, z)$ and $y_0 \equiv g(0, z)$ be the potential outcomes corresponding to the two mutually exclusive states of use and non-use of credit, respectively. For any population unit, the causal effect of use of credit on the outcome *y* is defined as: $y_1 - y_0$. However, the two potential outcomes cannot be observed at the same time. With the observed outcome *y* given by $y = D_j y_1 + (1 - D_j) y_0$, we can only observe either y_1 or y_0 depending on whether D_j equal 1 or 0, thus making it impossible to measure $y_1 - y_0$ for any population unit. However, if we let Y be the random variable defined in some probability space $(\Omega, \Sigma, \mathrm{P})$ reflecting the distribution in the population of the outcome represented by the outcome variable y[1], then the average causal effect of adoption in the population, $E(Y_1 - Y_0)$ (with E being the mathematical expectation operator), can be determined. Such a population parameter is called the average treatment effect (ATE) in the literature. One can also estimate the mean effect of the use of credit on the sub-population of users of credit: $E(y_1 - y_0 \mid D_j = 1)$, which is called the average treatment effect on the treated and is usually denoted by ATT. The average treatment effect on the *untreated*: $E(y_1 - y_0 \mid D_j = 0)$ denoted by ATU is another population parameter that can be defined and estimated.

The population means impact parameters ATE, ATT, ATU can generally be identified under some statistical independence assumptions between the population distributions of the treatment status variable D and the two potential outcomes Y_1 and Y_0 (possibly conditional on some observed random vector X of covariates). Two alternative statistical independence assumptions are made to identify ATE, ATT and ATU (Imbens and Wooldrige, 2009) [2]. The first one is the *unconditional independence* assumption: The population distribution of D is independent of that of Y_1 and Y_0. Under this assumption, ATE, ATT and ATU are identified by the mean difference of observed outcomes of users of credit and non-users of credit:
MD=$E(Y \mid D=1) - E(Y \mid D=0)$, which is easily estimated by its sample analogue. The second assumption is the *conditional independence* assumption also called "selection on observables", whereby the population distribution of D is independent of that of Y_1 and Y_0 conditional on some observed component X of the vector $(a^*_{(\dot{N})}, Z)$ of exogenous and endogenous random variables whose values do not depend on $a_{\dot{N}}$. Under this assumption the conditional mean treatment effects are all identified by the conditional mean difference of observed outcomes MD(x) = $E(Y \mid X = x, D=1) - E(Y \mid X = x, D=0)$ and ATE, ATT and ATU are identified by the mean of MD(x) over x in the full population, the subpopulation with D=1 and the subpopulation with D=0, respectively. Several estimators are used to estimate MD(x) (Imbens and Wooldrige, 2009; Imbens, 2004). These include: 1) matching estimators (nearest neighborhood covariates matching, propensity score matching, genetic matching and coarsened exact matching, etc.); 2) regression-based estimators including parametric (OLS/NLS) and non-parametric (kernel, polynomial series, etc.); 3) inverse probability weighting (IPW) estimators; and 4) hybrid estimators which combine matching and regression or IPW and regression (the doubly robust estimator).

However, in the case of an endogenous treatment like the use of credit, the assumption of conditional or unconditional independence is a very unrealistic assumption. Instead, the most

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[1] That is, Y takes its values in the same outcome space as the deterministic outcome function $g(a_{\dot{N}}, z)$ that determines the value of *y*. Similarly, from now on, we will use the same probability space (Ω, Σ, P) and use corresponding capital letters to designate the random vectors corresponding to the lower case vector defined above. In particular, *D* and Z will stand respectively for the binary random variable corresponding to *d* and the random vector corresponding to the vector z.

[2] These independence assumptions are accompanied by some regularity conditions on the support of the conditional and unconditional distribution of D (see Imbens and Wooldridge, 2009)

plausible assumption in this case is the "selection on unobservables". But, in the case of "selection on unobservable", the ATE, ATT and ATU parameters cannot be identified without making additional arbitrary assumptions about the functional form of the outcome function and probability distribution of the unobserved variables (Heckman and Vytlacil, 2005). For this case, Imbens and Angrist (1994) have introduced the *local average treatment effect* (LATE). LATE assumes the existence of at least one instrumental variable *V* that explains treatment status but is redundant in explaining the outcomes Y_1 and Y_0. LATE is defined as the *mean impact in the subpopulation of "compliers"* (population units who were induced to change treatment status by the instrument *z)*: *LATE*= $E(y_1 - y_0 \mid C(z))$, where $C(z)$ is the complier subpopulation with respect to *z.*

Under all circumstances (unconditional independence, "selection on observables" or selection on unobservables"), the LATE parameter can be identified using instrumental variables (IV) methods (Heckman and Vytlacil, 1999 and 2005; Heckman and Robb, 1985; Manski and Pepper, 2000; Imbens, 2004; Abadie, 2003; Imbens and Angrist, 1994), which are designed to remove both overt and hidden biases and deal with the problem of endogenous treatment. The IV-based methods assume the existence of an instrument called *z*, that explains treatment status but is redundant in explaining the outcomes Y_1 and Y_0, once the effects of the covariates *x* are controlled for. Different IV-based estimators are available, depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities.

The first one is the simple non-parametric Wald estimator proposed by Imbens and Angrist (1994), which supposes that the instrument z is random and totally independent of the potential outcomes Y_1 and Y_0. It requires only the observed outcome variable y, the treatment status variable D, and an instrument z. The second IV-based estimator is Abadie's (2003) Local Average Response Function (LARF) which generalizes the LATE estimator of Imbens and Angrist (1994) to cases where the instrument z is not totally independent of the potential outcomes Y_1 and Y_0 but will become so, conditional on x, a vector of covariates that determines the observed outcome y.

In this study, the instrument we used is *having obtained credit*. Obtaining credit by a farmer can explain the use of credit in rice production, but it is redundant in explaining the two potential states of productivity and incomes. The assumption that obtaining credit is random in the population is, however, unrealistic given the way farmers are aware about credit institutions and criteria for having access to credit. Therefore, we used Abadie's (2003) LARF to estimate the LATE parameter for assessing the impact of the use of credit in rice farming on yield and income. In the study, we also checked for the homogeneity of the impact by disaggregating the impact over the gender of farmers. Moreover, we analyzed the different livelihood improving strategies used by farmers when using credit in rice farming by assessing the impact of the use of credit on inputs demand.

2.3. Data and descriptive statistics

In accordance with the recommendation of statisticians, as revealed by Khandker *et al.* (2010), this study adopted a two-step stratification approach to improve the internal and external validity. In the first step, villages were selected from Communes and, in the second stage, famers from villages. Only one rice farmer was selected per household. This allowed us to collect household-level information. The importance of rice and the accessibility of the village were the main criteria used for the village selection. Villages were randomly selected from each group of villages based on the importance of each group. In total, 35 villages were selected: 22 in the central region and 13 in the northern region. On average, 10 rice producing households were randomly selected from each village and 361 such households were surveyed for the *ex-post* impact assessment study. However, due to problems with the quality of data, only 342 households were used.

Data were collected at village and producer levels in 2010. The data are related, among others, to socio-demographic characteristics of farmers, obtaining of credit in cash during the last rice cropping season, obtaining of credit in kind during the last rice cropping season, activities in which the credit is used (including rice farming), land size available, rice area cultivated, quantity and cost of inputs used (seed, fertilizer, pesticides, labor, hired labor), rice production, rice selling price, revenues and expenses related to other activities and other household members, household assets, children's schooling and health, main foods consumed by household members, etc.

Obtaining credit means that a rice farmer reports having received credit during the last rice farming season from any source of credit. Farmers were asked the following questions: *'Did you obtain credit in cash during the last three years?*' and *'Did you obtain credit in kind (seeds, fertilizers, pesticides, etc.) during the last three years?*' The credit that we focused on is not a specific activity-oriented credit or specific-actor oriented credit, but any credit in general that farmers manage to get from any source (financial or micro-credit institutions, public credit institutions, extension services, private institutions, etc.). The two dummy variables obtained were combined to a single dummy variable 'Obtaining credit' which expresses the obtaining of credit in cash or in kind by a given farmer. This variable is equal to 1 if the farmer has received credit (in cash or in kind) and 0 otherwise. Similarly, the use of credit is the fact that a farmer reports to have used the credit obtained in rice farming activity during the last rice farming season. Farmers were asked the following questions for each type of credit: '*In which activity have you used the credit obtained?'* The optional answers suggested to farmers included rice farming activity. The codes of using credit in rice farming were used to generate the two variables related to the use of credit in cash in rice farming and the use of credit in kind in rice farming. A single dummy variable '*Use of credit in rice farming activity'* was generated from these two variables expressing the use of credit (in cash or in kind) in rice farming. This variable is equal to 1 if the farmer used credit (in cash or in kind) in rice farming and 0 otherwise. The variable 'obtaining credit' will be used as an instrumental variable in the estimation of the LATE parameter whereas the variable 'use of credit in rice farming' will be used as a treatment variable.

3. Results and Discussion

3.1. Socio-demographic characteristics of rice farmers

Table 1 reveals that the majority of respondents (64.72%) are female farmers. Only 38.9% of farmers obtained credit with the highest rate for female farmers (43.0% against 31.4% for male farmers). In addition, all rice farmers who got credit did not use it in rice farming. The rate of use of credit was estimated at 29.0% (73.7% of those who got credit) with 30.3 % for female farmers and 26.5% for male farmers. Credit users in rice farming (44 years old) are younger than credit non-users (47 years old). The average household size of credit users (6.24 people) is statistically higher than for non-users of credit (5.62 people). In addition, credit users spent less time in their villages (35 years) than the non-users of credit (40.66 years). Among users of credit, 29.53% had primary school education against 15.9 % for non-users of credit. Furthermore, users of credit used more ICT / media tools than non-credit users - 79.55% listened to the radio (against 63.76 % for non-users of credit) and 61.36 % owned a mobile phone (against 35.9 % for non-users of credit). Most of the users of credit belonged to an association (84.09%) and were in contact with the rice extension institution (59%).

3.2. Mean differences analysis of inputs and outcomes by treatment status

Evidence from Table 2 shows that users of credit cultivated larger rice farms (0.82 ha) than non-users (0.63 ha). This difference was more pronounced among male farmers (+0.56 ha) than female farmers (+0.04). The average rice farm size of male users of credit (1.36 ha) was more than twice that of female users of credit (0.56 ha).. Female users of credit used less labor (535.6 man-days per hectare) than female non-users of credit (808.8 man-days per hectare). However, there was no significant difference between users and non-users of credit in terms of quantity of fertilizer applied per hectare, cost of hired labor per hectare and quantity of pesticides used per hectare. Based on these findings, one can conclude that the use of credit allowed farmers to increase only the size of their rice farm. However, as explained above, the mean difference cannot give the true effect of the use of credit on input demand.

Moreover, mean differences in outcomes (Table 3) show significant (at 10% level) and positive differences between users and non-users of credit in rice farming only for rice income and household income per capita. This reveals that users of credit gained more from rice production than non-users of credit did. The intra-gender analysis shows significant and positive differences between users and non-users of credit only among male farmers for rice income, rice income per capita and household income per capita.

3.3. Impact of use of credit on rice yield and its determinants

Table 4 gives the LATE estimates for rice output and yield. The LATE values are all positive and significant at 1% level, indicating that the use of credit in rice farming has a positive and significant impact on rice output and yield. Users of credit harvested an additional 70.8 kg (157.2 kg per hectare) of paddy. This trend is confirmed by Hulme and Mosley (1996), Rasoloarison *et al.* (2001), Diagne (2002), Fall (2008), Das *et al.* (2009), Bolarinwa and Fakoya (2011) and Ayaz and Anwar (2011) who found, in studies assessing the impact of agricultural credit, positive and significant impacts of agricultural credit on agricultural output, yield and technical efficiency. In addition, the results show that the increases in rice output and yield are higher among female farmers than male farmers. Female users of credit increased their total rice output by 93 kg of paddy (against 36 kg for male users of credit) and their rice yield by 177 kg per hectare (against 126 kg for male users of credit). Thus, the impact of the use of credit in rice farming was not homogenous across genders and was more profitable for female rice farmers. This heterogeneity of the impact on productivity was also reported by Hulme and Mosley (1996), Fall (2008) and Diagne (2002).

The determinants of rice output and yield as given by the LARF are presented in Table 5. These estimates provide evidence that, apart from a change in credit use, other household socio-demographic variables significantly explain the change in rice output and yield. Household size, watching television and training in agriculture contributed to increased rice output while practicing a secondary activity reduced it. Rice yield was improved by household size, watching television, training in agriculture and a secondary activity but reduced by primary school education.

3.4. Impact of use of credit on rice income and annual household income and their determinants

The LATE values presented in Table 6 are all positive and statistically different from zero, indicating that the use of credit has a positive and significant impact on the rice income and rice income per capita. Thus, users of credit increased their rice income on average by 50,974 F CFA ($US107.79) [3] and per capita rice income by 1,546 F CFA ($US3.27). For both rice income and per capita rice income, the impacts were higher among female farmers (59,225 F CFA or $US125.24 and 1,709 F CFA or $US3.61 per capita) than among male farmers (37,087 F CFA or $US78.42 and 1,271 F CFA or $US2.69 per capita). In other words, female users of credit earned more from using credit in rice farming than their male counterparts. The LARF estimation of the determinants of rice income is summarized in Table 7. Rice income

[3] Conversion rate : 1 USD =472.89 (BCEAO on 11 March 2014)

tended to be higher with living in a village hosting a participatory varietal selection trial, contact with an NGO and contact with the national agricultural research institute (INRAB) and lower with the number of years of experience in rice farming.

Table 6 also gives LATE estimates for annual household income and per capita annual household income. As previously, LATE values are all positive and statistically different from zero, revealing that the use of credit also had a positive and significant impact on annual household income and per capita annual household income. Thus, users of credit improved their annual household income on average by 141,184 F CFA ($US298.56) and gained an average surplus per capita of 13,235 F CFA ($US28). Furthermore, the impacts on both annual household income and per capita annual household income were not homogenous across genders and were higher for female users of credit (151,470 F CFA or $US320.31 and 14,081 F CFA or $US29.78 per capita) than for male users of credit (122,334 F CFA or $US258.69 and 11,686 F CFA or $US24.71). In other words, the households of female users of credit gained more from using credit in rice farming than their male counterparts. In addition, LARF estimation for annual household income (Table 7) shows that annual household income was increased by the use of credit, practicing upland rice farming and contact with INRAB but decreased by practicing a secondary activity and living in a village hosting a PVS trial.

3.5. Impact of use of credit on inputs demand

The objective of this section is to analyze the inputs utilization choices made by farmers due to the use of credit, and check whether there is a difference which can explain the heterogeneity in the impact. The results in Table 8 show that access to credit improved farmers' use of inputs in rice farming and reduced financial constraints faced by them in accessing certain inputs (Djato, 2001 ; Haidara, 2001 Hounlonkou *et al.*, 2005; Kudi *et al.*, 2009; Fall, 2008; Bolarinwa and Fakoya (2011). The use of credit in rice farming induced an increase in the rice area cultivated (+0.15 ha), the quantity of fertilizer used per hectare by rice farmers (+38.33 kg) and the cost of hired labor (+8 925 FCFA). It also enabled farmers to optimize the use of labor by reducing the time spent in rice production activities and increasing the use of hired labor, generally more skilled, and therefore more efficient. Also, the use of credit has no significant impact on the demand for seed. However, the impacts of the use of credit in rice farming varied from one input to another and across genders. In other words, male and female rice farmers chose different strategies in using credit in rice farming to improve their productivity. Thus, male farmers mostly increased their rice farm size (+0.21 ha) and invested in hired labor (+15 541 F CFA per hectare), while female farmers invested more in purchasing fertilizer (+60.35 kg per hectare), and reducing both working time (-255.94 man-days per hectare on average) and the amount of seed used (- 1.44 kg per hectare). This heterogeneity in the choices of inputs utilization made by farmers contributes to the heterogeneity found in the impacts of the use of credit on productivity and income. These findings confirm the importance of taking into account the heterogeneity of the impact in any impact assessment study.

Considering the crucial role played by women in their households, these findings reveal that the higher income gained by female users of credit can effectively improve households' livelihood in general and children's livelihood in particular. Thus, mitigating the constraints related to access to credit and its use in rice farming would truly improve rice farmers' productivity, income and their households' livelihood, and therefore contribute to rural poverty alleviation. However, many studies have confirmed the heterogeneity of the impact of credit and showed that the effects of mitigating constraints of access to credit may vary from one social stratum to another. According to Kpadonou *et al.* (2010), who used Discrete Stochastic Programming to assess the impact of credit constraints on income and agricultural production, the increase in income resulting from the contribution of an additional CFA of credit differs across the social stratum as follows: 2.62 F CFA for small, 0.76 F CFA for medium and 0.55 F CFA for large farms. Thus, the increase in income was higher on small farms than on large farms. In contrast, Fall (2008), Hulme and Mosley (1996) and Diagne and Zeller (2001) showed lower impact for poor farmers. Indeed, Fall (2008) assessed the impact of access to credit on technical efficiency and income in irrigated systems in Senegal and showed that the impacts were almost nil for the poorest farmers but positive and significantly different from zero for less poor and 'rich' farmers who have other sources of income for procuring inputs. In the same vein, Hulme and Mosley (1996) found a positive and significant impact of credit for farmers who already have a certain level of resources, income and physical assets, while the impact was very low or negative for the poorest clients of microfinance institutions. The explanation gave was that the amount of loans taken by poor borrowers is insufficient for increasing their productivity. Diagne and Zeller (2001) assessed the impact of access to credit on welfare in Malawi and showed that some farmers are so poor that they cannot significantly improve their productivity with access to inputs. They added that the contribution of rural microfinance institutions to the income of smallholders can be limited or outright negative if the design of the institutions and their services do not take into account the constraints on and demands of their clients. Diagne and Zeller (2001) also reported that when some households choose to borrow, they realize lower profit than those who choose not to borrow. Although this result was not statistically significant, it nevertheless highlights the risk of the loan: Borrowers may be worse-off after repaying the principal and the interest. Therefore, Koloma (2010) proposed some thresholds to be met to avoid microfinance leading households into indebtedness. In conclusion, access to credit and its use in agricultural activities is very profitable and advantageous for smallholders. However, these benefits depend on some agro-ecological and socio- economic factors that may vary over time and space.

4. Conclusions and suggestions

Credit is a very important tool for agricultural development in developing countries. This paper was initiated to quantify the importance of credit in rice farming in Benin by assessing the impact of the use of credit on rice yield and household incomes. The potential outcome framework was utilized to estimate the local average treatment effect (LATE). The findings reveal that 38.9% of farmers obtained credit in cash or kind with a higher rate for female farmers. In addition, all rice farmers who managed to get credit did not use it in rice farming. The rate of use of credit was estimated at 29.0 % with 30.3 % for female farmers against 26.5% for male farmers.

In addition, the use of credit in rice farming had a positive and significant impact on rice yield (+157.2 kg/ha), rice output (+70.8 kg), total rice income (+50,974 F CFA or $US107.79), per capita rice income (+1546 F CFA or $US3.27 per capita), annual household income (+141,184 F CFA or $US298.56), and per capita household income (13,235 F CFA) of rice. Access to credit enabled users of credit in rice farming to improve their inputs utilization (rice land, fertilizer and labor) in order to increase not only their yields and rice output, but also their rice income and annual household income. Thus, credit has been found to be important to both rice farmers and rice sector development. These findings suggest that facilitating access to credit by farmers is a good strategy for enhancing rice farmers' productivity and incomes. Therefore, to contribute to rice sector development, governments, MFIs and development partners should work together to improve access by rice farmers to suitable agricultural credit (in kind/ in cash), including a review of interest rates. The government should be encouraged to pursue and improve all its microfinance initiatives targeting agriculture in general, and rice production in particular. The program on Micro-credit to Poorest, which is becoming the main provider of micro-credit to women, could better contribute to poverty reduction if it was activity-based with a higher amount of credit. Furthermore, MFIs should be encouraged to be more familiar with the agricultural sector and farmers' financial needs and adapt their products to these needs. Moreover, information communication technology tools, the media and agricultural extension services may also be used to inform farmers about credit opportunities, the name and location of MFIs which can provide appropriate credit to them, the procedure for applying for loans, and the risks involved in taking loans. All these strategies could improve the access by farmers in general, and rice farmers in particular to suitable credit. This would contribute to the intensification of rice production in Africa to meet increasing rice demand, and improve rice farmers' productivity and household incomes, thereby contributing to food security and poverty alleviation in Africa in general, and in Benin in particular.

Moreover, the results indicate that the impacts of the use of credit in rice farming are not homogenous among rice farmers. For all the impact indicators mentioned above, the female users of credit gained more from using credit in rice farming than their male counterparts. Therefore, when assessing the impact of development interventions on beneficiaries, it is important to take into account the heterogeneity of the impact for a better appreciation of the real effects of the intervention on the different social categories in the target population. The LATE estimation method used in this study takes into account this heterogeneity by including the interaction terms (interaction of covariates with the treatment variable).

Appendices

Table 1: Socio-demographic characteristics of rice farmers over status of use of credit

	Pool (342)		Male (121)		Female (221)	
Variables	UC (98)	NUC (244)	UC (31)	NUC (90)	UC (67)	NUC (154)
Age	44.39** (10.57)	47.41 (12.31)	47.51 (11.04)	47.42 (12.31)	42.94*** (10.10)	47.41 (12.35)
Household size	6.24* (2.56)	5.62 (2.74)	7.19 (2.79)	6.43 (3.19)	5.81* (2.34)	5.15 (2.32)
Years of residency in village	35.02*** (16.33)	40.66 (16.28)	41.74 (17.74)	43.62 (15.26)	31.91*** (14.75)	38.92 (16.65)
Attending primary school	29.53* (45.69)	15.90 (36.99)	53.15 (50.13)	40 (51.64)	15.51* (36.30)	8.82 (28.79)
Number of years of schooling	1.56 (2.78)	1.27 (3.04)	3.5 (4.65)	2.90 (3.33)	0.76 (2.02)	0.61 (2.06)
Agricultural training	56.81 (50.11)	52.35 (50.03)	100*	60.36 (49.14)	47.59 (50.07)	44.12 (50.40)
Upland rice farming	25 (43.80)	23.83 (42.67)	50 (52.70)	28.82 (45.50)	20.86 (40.74)	17.65 (38.70)
Lowland rice farming	89.26 (31.01)	86.36 (34.71)	90 (30.01)	80 (42.16)	88.77 (31.66)	88.23 (32.70)
Listening to radio	79.55** (40.80)	63.76 (48.15)	100	80.18 (40.04)	73.52** (44.78)	54.01 (49.97)
Owning mobile phone	61.36*** (49.25)	35.9 (48.05)	80* (50.45)	50.45 (50.22)	55.88 (50.40)	27.27 (44.65)
Relationship with public extension services	59.09** (49.73)	40.94 (49.25)	90*** (31.62)	48.64 (50.21)	50*** (50.75)	36.36 (48.23)
Belonging to an association	84.09 (36.99)	75.84 (42.88)	90 (31.62)	80.18 (40.04)	82.35 (38.69)	73.26 (44.38)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 2: Inputs used by farmers over status of use of credit

	Pool (342)		Male (121)		Female (221)		
	UC (98)	NUC (244)	UC (31)	NUC (90)	UC (67)	NUC (154)	UC (98)
Rice area cultivated (ha)	0.82* (0.80)	0.63 (0.84)	0.68 (0.83)	1.36*** (1.11)	0.81 (0.93)	0.56 (0.43)	0.52 (0.76)

Quantity of seeds per hectare (kg/ha)	59.09 (29.62)	62.12 (31.86)	61.24 (31.22)	60.26 (26.25)	60.09 (60.09)	58.53 (31.28)	63.29 (32.05)
Quantity of fertilizer per hectare (kg/ha)	255.51 (291.45)	213.83 (382.42)	225.90	273.18 (497.60)	222.28 (231.03)	247.07 (298.05)	247.07 (317.55)
Quantity of total labor per hectare (man-day/ha)	594.08 (1311)	711.21 (865)	677.30 (1014)	716.60 (2210)	542.29 (720)	535.57** (499)	808.83 (927)
Cost of hired labor per hectare (F CFA/ha)	37394 (55073)	39525 (111587)	38908 (98535)	25065 (32470)	40656 (149554)	43283 (62446)	38871 (82638)
Quantity of pesticides per hectare (L/ha)	2.76 (15.8)	0.68 (8.1)	1.28 (10.9)	8.22 (44.1)	0.57 (3.0)	0.97 (4.0)	0.23 (2.1)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 3: Mean differences analysis for rice yield and income and household income

	Pool (342)		Male (121)		Female (221)	
	UC (98)	NUC (244)	UC (31)	NUC (90)	UC (67)	NUC (154)
Production (kg)	1440.68	1104.53	2233.13*	1506.01	1074.03	869.90
	(1500.88)	(2011.58)	(1853.21)	(2011.07)	(1148.14)	(1980.89)
Rice yield (kg/ha)	2007.84	1841.65	1953.43	1974.63	2033.02	1763.93
	(1074.84)	(1124.06)	(1034.68)	(1112.73)	(1098.87)	(1175.96)
Rice income	131274.27*	97134.60	221772.69*	134628.34	93095.25	75355.14
	(183071.4)	(145316.37)	(293035.28)	(202178.41)	(86311.81)	(92500.3)
Rice income per capita	36942.01	27171.11	66043.71**	26120.722	23477.049	27784.975
	(103727.44)	(59108.65)	(177999.54)	(34315.30)	(28800.07)	(69735.41)
Household income	473728.05	343560.94	786417.36	424487.07	329050.9	296266.45
	(596105.27)	(486804.55)	(890810.82)	(432998.94)	(307196.16)	(511089.45)
Household income per capita	61573.07*	48353.18	79482.16***	52533.35	54017.67	45924.99
	(45243.72)	(40709.19)	(46633.26)	(44149.48)	(42794.28)	(38531.44)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 4: LATE estimates for rice output and rice yield

	LATE for rice output (kg)	LATE for rice yield (kg/ha)

Pool	70.80 *** (18.04)	157.17 *** (12.88)
Male farmers	35.97 *** (17.69)	126.25 *** (20.81)
Female farmers	93.03 *** (27.0)	176.91 *** (10.78)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 5: LARF estimates of determinants of rice output and yield

Variables	Rice output (kg)	Rice yield (kg/ha)
Use of credit in rice farming	573 (812)	1010** (812)
Growing rice in upland ecology	411 (409)	45 (219)
Contact with extension services	479 (432)	-134 (231)
Attending primary school	-295 (353)	-389** (189)
Household size	164*** (55)	33*** (29)
Watching television	1887*** (507)	10*** (271)
Receiving training in agriculture	668* (345)	750*** (185)
Practicing secondary activity	-584* (327)	369** (174)
Growing rice in upland ecology _use of credit	606 (597)	-176 (319)
Contact with extension services _use of credit	-335 (665)	358 (356)
Attending primary school _use of credit	676 (632)	143 (338)
Household size _use of credit	-97 (98)	-53 (53)
Watching television _use of credit	-1968 * (732)	-298 * (392)
Receiving training in agriculture _use of credit	-329 (551)	-795*** (295)
Practicing secondary activity _use of credit	886 (537)	-544** (287)
Constant	-495 (494)	1234*** (264)
Number of observations	*252*	*252*
R-squared	*0.1737*	*0.1311*
Adj R-squared	*0.1248*	*0.0797*

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 6: LATE estimates for rice income and annual household income (F CFA)

	Rice income	Rice income per capita	Annual household income	Per capita annual household income

Pool	50974 *** (1435)	1546*** (316)	141184 *** (4764)	13235*** (182)
Male farmers	37087*** (4877)	1271 (1094)	122334*** (10457)	11686*** (269)
Female farmers	59225*** (856)	1709*** (380)	151470*** (3374)	14081 *** (268)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*

Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 7: LARF estimates of determinants of rice income

Variables	Rice income (F CFA)	Annual household income (F CFA)
Use of credit in rice farming	3295 (33867)	86438 (79456)
Growing rice in upland ecology	-15616 (24052)	130615** (59271)
Watching television	-55683 (34024)	-97298 (103629)
Practicing secondary activity	-49758** (20091)	-112961** (49206)
Living in a PVS village	100703*** (20722)	74127 (52135)
Contact with NGOs	93104 *** (29013)	84542 (73564)
Number of years of experience in rice farming	-1762** (878)	-2885 (2175)
Contact with INRAB	234032** (103680)	1007359***(372608)
Growing rice in upland ecology _use of credit	107993*** (35623)	-1921 (86386)
Watching television _use of credit	62609 (47203)	65526 (130065)
Practicing secondary activity _use of credit	59506* (33265)	284363*** (79378)
Living in a PVS village _use of credit	-76706** (3466)	-180958** (84797)
Contact with NGOs _use of credit	-87851* (48217)	-223099* (119176)
Number of years of experience in rice farming _use of credit	1212 (1478)	-179 (3531)
Contact with INRAB _use of credit	-227241 (160807)	29759 (468032)
Constant	93938 *** (22496)	252556 *** (53306)
Number of observations	*245*	*225*
R-squared	*0.2210*	*0.2422*
Adj R-squared	*0.1727*	*0.1916*

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*
Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

Table 8: LATE estimates on inputs demand

	Rice area cultivated (ha)	Quantity of fertilizer (kg per hectare)	Quantity of seed (kg per hectare)	Total labor (man-days per hectare)	Cost of hired labor (F CFA per hectare)
Pool	0.15** (0.071)	38.33 *** (3.81)	-0.95 (0.81)	-180. 80*** (29.88)	8925*** (7412)
Male farmers	0.21** (0.090)	3.85 (9.33)	-0.20 (0.97)	-61.76 (43.46)	15541*** (1380)
Female farmers	0.12** (0.069)	60.35 *** (3.36)	-1.44 * (0.86)	-255.94 *** (28.27)	4748*** (650)

*Legend: Standard errors are in brackets; ***=Significant at 1%, **= significant at 5%, *=significant at 10%.*

Source: AfricaRice/PAPA 2010, NERICA impact assessment survey.

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