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The Effect of Credit Constraints on Crop Yield: Evidence from Soybean Farmers in Northern Region of Ghana

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Abstract

Many farmers request for production credit to improve farm productivity, but are often denied by financial institutions. The rational questions to ask are: What factors characterize farmers who get denied of production credits? Does credit constraint lead to lower yield? This study aims to answer these important but often overlooked questions. A multistage sampling technique was used to select a cross-section of soybean farmers who applied for production credit in the Yendi Municipality and Saboba district of the Northern region of Ghana. A binary probit model is used to examine farmers who get denied of production credit. Correcting for sample selection bias, a propensity score matching is used to examine the effect of credit denial on crop yield. Results are very conclusive, and we find that farmers who are often denied access to production credit significantly lack prior training on their enterprises. In addition to that, farmers who are not members of FBOs, have their own buyers for their produce, have low experience, have no formal education, make no savings from their farm activities and are without access to credit information are more likely to be refused credit when applied. Refusing credit to farmers constrains their farm operations and makes them less productive. Policy implications are enormous; farmers would need to participate in training programmes on crop enterprises to increase chances of receiving credit from lending institutions; governments would need to intensify extension programmes where extension agents can facilitate farmer training.

Keywords: *Credit Constraints, Propensity Score Matching, Soybean Production, Northern Ghana*

INTRODUCTION

The Food and Agricultural Sector in Ghana is still very important for national economic development on two main scores: first, it contributes about 22% to gross domestic product; second, it employs about 60 percent of the active labour force. Eighty percent (80%) of the agricultural labour force are smallholder farmers, who produce over twothirds of national food production. Smallholder farmers are involved in the production and marketing of food crops and livestock products needed for the nourishment of both rural and urban dwellers. Many empirical studies have indicated that the productivity of smallholder farmers depends on the use of improved methods of agricultural production (Baffoe and Matsuda, 2015, Abdulai and Huffman, 2005, Khonje et al., 2015, Villano et al., 2015, Liverpool-Tasie et al., 2015, Larson et al., 2016, Hozayn et al., 2016, Zhang et al., 2016, Nin-Pratt, 2016, Muzari et al., 2012, Donkoh and Awuni, 2011). These improved or modern production methods often need to be accompanied by the use of purchased inputs in order to realize the full potential and contribution to agricultural productivity. For example, Donkoh (2011) and Fan et al. (2012) have found that productivity of crops are increased through the use of purchased inputs such as improved seeds, inorganic fertilizers, pesticides and fungicides. In relation to the use of purchased inputs, many smallholder farmers are frequently severely constrained by capital to afford them. Generally, smallholder farmers are not able to save from previous production to invest in current production. Naturally, the subsistence nature of their production activities may make savings difficult. Many farmers use the greater part of their output for consumption, thus leaving little or none for sale to generate income. So, in effect there is a cyclical pattern of subsistent production, consumption and limited or non-savings. Given that access to markets exist, then a potential pathway to break this vicious cycle involves assisting farmers to produce on large scale beyond subsistent needs so that cash can be generated, savings made from the income and investments can be made thereof. This is one of the main thrusts of governments, development actors and donor agencies in developing countries.

The provision of credit is widely perceived as a more viable pathway to helping smallholder farmers overcome capital constraints (Karlan et al., 2014, Dzadze et al., 2012, Freeman et al., 1998). But credit provisioning in Ghana for agricultural purposes has obviously been inadequate and inequitable. Oftentimes, the numerous small scale farmers who supply the bulk of Ghana’s food needs are denied of production credit. This makes them constrained in their production activities. Ghana’s Second Food and Agricultural Sector Development Policy (FASDEP II) document emphatically acknowledges the role that credit can play in productivity and livelihood improvements. The paper first recognises and highlights internal and external factors that limit farmers’ access to credit. Internal factors concerns lack of collateral and ownership of assets, particularly for women farmers, poor financial management and risky nature of farming as well as inability of clients to prepare viable project proposals. External factors are mainly as a result of high interest rates, high cost of service delivery to the sector and perception of financial services providers about farming as being high risk. The multiplier effect of credit constraint and access is enormous. First, it limits demand for agro-inputs, leading to low use of improved methods which eventually leads to unsustainable land and environmental management. Second, low productivity caused by limited use or non-use of improved methods leads to extended and expanded cases of poverty and food insecurity (Akudugu, 2014).

The national vision for the Food and Agriculture Sector, is to achieve structural transformation through modernization of agriculture for improved food security, employment opportunities and reduced poverty. This requires farmers to use improved techniques and production methods such as improved crop varieties, animal breeds, fertilizer application and agrochemicals in general, in order to facilitate technical change (MoFA, 2007). Also, the transition from a lower production frontier to a higher one is normally achieved through technological change, which requires farmers to make a transition or switch from the use of traditional techniques to modern ones. Farmers would only rationally respond to technological change if they have the requisite capital to invest in these techniques. For a long time, farmers have depended on their meager farm incomes to finance agricultural production operations. The practice of farmers depending on income from their past production activities to finance current production has not been effective and sustainable. According to Conning and Udry (2007), farmers find it difficult to balance their production budget because of the extensive time lag involved in transforming agricultural inputs into output. In terms of credit, smallholder farmers often face binding constraints. Theoretically, farmers who face binding capital constraints often tend to use less than optimal levels and combinations of inputs compared to farmers whose production activities are unconstrained by capital. If such constraints are not addressed, the resultant sub-optimal use of production resources leads to low productivity and inefficiencies in agricultural systems (Freeman et al., 1998).

The forgoing suggests that credit provisioning to smallholder farmers is an important pathway to improve livelihood and food security. A comprehensive review of credit access and its various determinants as well as implications for agricultural transformation in developing countries is provided by Yadav and Sharma (2015). According to the Bank of Ghana’s Policy document on Agriculture (GoG, 2004), over the years the formal and informal sources of credit for agricultural production have not yielded significant impacts on credit availability to the sector. The reason is that lending institutions are highly cautious and reluctant to advance credits to qualified and/or deserving smallholder farmers. Their fears border on low recovery rates, for which the concerned officials would be held responsible in case of defaults. Even with the limited number of formal sources of financing, the information asymmetry associated with financing agriculture causes the lenders to screen different loan applications to determine who is more likely to repay. Lenders may also have to monitor the use of funds to ensure that credits advanced for specific purposes are channeled into the exact purpose in order to increase the chances of repayment (Von Pischke, 1991). In most cases, the credit is rationed, and this keeps potential beneficiary farmers out of the credit market even though many of them might propose good investments to the financial institutions. Many smallholder farmers who apply for agricultural credits from the lending institutions are usually denied. Our argument is that farmers who apply for agricultural credit may genuinely need this to increase productivity, but are often denied. This amounts not only to economic costs but also a social cost because there is sub-optimal use of the national and natural resources such as land and labour. Whether farmers who apply for agricultural credit would be granted or not depends on several factors. Given that specific crops, e.g. soybean, are often cultivated to earn cash income, one would think that such farmers would be given credits to expand and improve production and productivity. Our research objective therefore, is to examine the characteristics of farmers who are likely to be denied agricultural credit and how this affects productivity.

A well-studied subject in relation to agricultural credit focuses on credit access, its determinant and farm productivity (Feder et al., 1990, Denkyirah et al., 2016, Akudugu, 2014, Akudugu et al., 2009, Baffoe and Matsuda, 2015, Dzadze et al., 2012). In this domain, empirical studies have found varied outcomes. Some have argued that limited availability of credit services has undermined the operations of rural micro-enterprise because they lack capital for investment. This constrains farmers from adopting improved seeds and other modern farming practices because they are not able to purchase requisite inputs in the production process (Schultz, 1965). Lawal and Abdulahi (2011) found that the informal financial sector in Kwara district of Nigeria impacted positively on agricultural production with rotating savings having the greatest impact, followed by periodic savings. Jing et al (2010) estimated that agricultural productivity and rural household income in China improved by 31.6% and 23.2%, respectively, with the removal of credit constraints. They found that access to credit ensured timely and adequate use of inputs for the implementation of all field operations by farmers. Awunyo-Vitor and Al-Hassan (2014), observed in the Brong Ahafo region of Ghana, that there is a positive impact of agricultural credit on maize productivity. However, Nosiru (2010) proved in his research article on the topic ‘Micro credits and Agricultural Productivity in Ogun State, Nigeria’, that micro credit did not lead to improvement in farm output. This, according to him, was as a result of non-judicious utilization, or diversion of credits obtained to other uses apart from the intended farm enterprises. This result is consistent with Siyoum et al. (2012) who found that access to credit did not enable poor households to increase their agricultural productivity and household food security. According to the authors, majority of the poor beneficiaries in their sample invested most of their loan in immediate consumption needs and, therefore, credit had no impact on increasing agricultural productivity. The credit helped poor households to cover seasonal food shortages with no impact on long-term productivity and household food security. They further explained that because poor households are risk averse, they are less likely to invest in agricultural productivity to improve their food security. Large numbers of better-off households, on the other hand, reported positively compared to the poor households. Credit enabled better-off households to buy additional oxen, seed, and fertilizer which helped them to increase their productivity (Chisasa, 2016).

While many studies on agricultural credit have examined questions from various perspectives, the issue relating to why potential credit seekers are denied by financial or lending institutions is less investigated. The contribution of this paper to the agricultural credit literature is founded on its focus on credit constraint as opposed to credit access. With access, some farmers may voluntarily opt out from application because they have excess savings or capital to invest in their farm businesses. The respondents used in this study all had positive demand for production credit and applied to lending institutions of some sort but some were denied while others were given. We argue that farmers who actually applied for credit from financial institutions have the desire to improve their production and productivity. Hence, denying such farmers of credit leads them to be constrained and their productive ventures may be adversely inhibited. Based on this dataset, we adopt a methodology that is suitable to account for any unobserved heterogeneity.

MATERIALS AND METHODS

Study area

The study was conducted in the Yendi Municipality and Saboba district located in the North-Eastern part of the Northern region of Ghana. Farmers in these districts are noted for producing large quantities of soybeans in the region. In recent times, these farmers have enjoyed interventions from both governmental and non-governmental organisations that target improving access to production credit. The study considered a cross-section of soybean farmers, and who have production data based on the 2015 production season. Purposive sampling technique was used to select 9 communities, based on the fact that they are the areas with considerable number of credit borrowers for agricultural production activities. Within each community, a simple random selection of households was made and respondents within selected for interview. Approximately, 30 soybean farmers were interviewed from each community, giving a total of 300 respondents. Out of these, 215 farmers had applied for credit of which 50.7% had received and 49.3% were denied. The remaining 86 respondents who were not used for this specific analysis were not credit constrained by our definition, hence were dropped from the analysis. They had their own excess capital to finance their farm operations.

A pre-tested questionnaire was used as the data collection instrument. The questionnaire sought to capture information relating to respondents' demography, social and economic characteristics as well as farmer and farm-specific information. Information relating to credit access, utilization and repayment were also recorded.

Data Analysis

Propensity Score Matching (PSM) Analysis to determine the effect of credit constraint on crop yield

PSM, as a modelling technique, helps to compare outcomes between two individuals; one is given a certain treatment and the other is denied of the treatment, either deliberately or not. In the context of this study, the PSM technique is used to compare the observed yield (output per acre) of soybean farmers who are credit constrained to the yield of counterfactual farmers given production credit based on the predicted propensity scores of having received the production credit (Rosenbaum, 2006, Rosenbaum and Rubin, 1983, Heckman et al., 1998, Smith and Todd, 2005). Two main steps are involved in this approach (Bernard et al., 2008, Erin M. Godtland et al., 2004). In the first step, propensity scores for all observations are calculated using a probit model. The essence of the propensity scores is to account for sample selection bias due to unobservable differences that may occur between treatment and comparison groups (Dehejia and Wahba, 2015). This step constructs a statistical comparison group by matching every individual observation in the credit constrained group with individual observations from the unconstrained farmers that have similar characteristics based on the propensity scores so calculated (Austin, 2011). In the second stage, the differences in the soybean yields of credit constrained and unconstrained farmers are calculated in terms of average treatment effect (ATE). The propensity scores generated in stage one are used to match treated observations (credit constrained farmers) with untreated observations (unconstrained farmers). The ATE is estimated as the mean difference in the response variable (yield) between credit constrained farmers, denoted by Y (1) and matched control group (unconstrained farmers), denoted by Y (0). Equation (1) represents the model to estimate the ATE.

$$\text{ATE} = E\left[Y(1) - Y(0)\right] = E\left[Y(1)\right] - E\left[Y(0)\right] \quad (1)$$

The ATE model compares the yield of farmers who were denied credit, even though they applied for it, with that of unconstrained farmers that are similar in terms of observable characteristics and also partially control for any selection bias that may arise. The ATE as calculated in equation (1) could be interpreted as the effect of credit constraint on soybean farmers' yield. We use this as a measure of productivity, so that a negative but significant value indicates that credit constrained farmers are less productive than their unconstrained counterparts, *ceteris paribus*.

Besides knowing the ATE, it is also important to calculate the average treatment effect on the treated (ATT) for the constrained farmers. The ATT model measures the effect of credit constraint on productivity for only farmers who are actually constrained rather than across all soybean farmers who could potentially be credit constrained. ATT is calculated using the expression in equation (2) as follows:

$$\begin{aligned} \text{ATT} &= \text{E}\left[\, \text{Y}(1) - \text{Y}(0) \,\middle|\, \text{D} = 1 \right] \\ &= \text{E}\left[\, \text{Y}(1) \,\middle|\, \text{D} = 1 \right] - \text{E}\left[\, \text{Y}(0) \,\middle|\, \text{D} = 1 \right] \end{aligned} \qquad (2)$$

where D is a dummy for treatment (D = 1 constrained, 0 for unconstrained). Finally, it is also good to have an idea of what productivity would be for constrained farmers if they were otherwise not constrained. This parameter is given by the average treatment effect on the untreated group (ATU). The model for measuring such ATU is expressed by equation (3) as follows:

$$\begin{aligned} \text{ATU} &= \text{E}\left[\, \text{Y}(1) - \text{Y}(0) \,\middle|\, \text{D} = 0 \right] \\ &= \text{E}\left[\, \text{Y}(1) \,\middle|\, \text{D} = 0 \right] - \text{E}\left[\, \text{Y}(0) \,\middle|\, \text{D} = 0 \right] \end{aligned} \qquad (3)$$

Since ATE, ATT and ATU are not observable (because they depend on counterfactual outcomes), there can often be the case that a hidden bias may arise. For instance, given that the average is the difference of the averages (see equation 2), $\text{E}\left[\text{Y}(0) \middle| \text{D}=1\right]$ is the average outcome that participants would have obtained in the absence of participation, which is not observed and $\text{E}\left[\text{Y}(0) \middle| \text{D}=0\right]$ is the value of $\text{Y}(0)$ for the untreated individuals. The difference Δ is calculated as: $\Delta = \text{E}\left[\text{Y}(1) \middle| \text{D}=1\right] - E\left[Y(0) \middle| D=0\right]$. The difference between Δ and ATT is:

$$\begin{aligned} \Delta &= \text{E}\left[\text{Y}(1) \middle| \text{D}=1\right] - E\left[Y(0) \middle| D=1\right] + \text{E}\left[\text{Y}(0) \middle| \text{D}=1\right] - E\left[Y(0) \middle| D=0\right] \\ \Delta &= ATT + \text{E}\left[\text{Y}(0) \middle| \text{D}=1\right] - E\left[Y(0) \middle| D=0\right] \\ \Delta &= \text{ATT} + \text{SB} \end{aligned} \qquad (4)$$

where SB is selection bias, which is the difference between the counterfactual outcomes for participant farmers and the observed outcomes for the non-participants. If this term is equal to zero then the ATE can be estimated by the difference between the mean observed outcomes for participants and non-participants as in equation (1).

Region of Common Support or Overlap Condition

Once the propensity score matching estimation is done, it is important to verify the common support or overlap condition. The assumption for this condition is that the probability that a soybean farmer is credit constrained lies between 0 and 1. The assumption is critical to the propensity score estimation, as it ensures that individuals with the same values on the characteristics have a positive probability of being both constrained and unconstrained statuses. Checking the region of common support between treatment and comparison groups can be done by visual inspection of the propensity score distributions for both the treatment and comparison groups. The visual check of overlap condition is to see whether matching is able to make the distributions more similar. If there exist unobserved variables which affect constrained status and the outcome variable simultaneously, a `hidden bias' might arise (Caliendo and Kopeinig, 2008). A sensitivity analysis of matching estimators can be used to test for unobserved heterogeneity (Duvendack and Palmer-Jones, 2012). Sensitivity analysis may be done to determine how strongly an unmeasured variable must influence the selection process in order to undermine the implications of matching analysis by creating a hidden bias.

Probit Model to Examine Credit Constrained and Unconstrained Soybean Farmers

Before estimating the impact of credit constraint on crop yield, first a binary probit model is used to examine the characteristics of credit constrained farmers. Credit constrained status is captured as a dummy variable (1 if farmer applied for production credit and was denied, 0 for farmers that applied and were given). Given two individual farmers, our interest lies in modeling the probability that when a given characteristic changes by a unit, one person would be given a credit while the other is denied. To do this, we use the latent variable approach (LVA) based on the probit specification. The probit model under the LVA, assumes that there is an unobserved continuous variable (y_i^*) relating to the observed characteristics ($\mathbf{X}$) about the individual farmers. It is assumed that larger values of the latent dependent variable increase the likelihood that a farmer who applied for credit would be denied. Thus, the Probit model is given by equations (5) as follows:

$$y_i^* = X_i^{'} b + e_i \tag{5}$$

where b is the coefficient vector of the parameters to be estimated, and the error component (e) is assumed to follow a standard normal distribution with mean zero and constant variance, so that the probit model becomes an ideal means to estimate the parameters through maximum likelihood.

$$y_i = \begin{Bmatrix} 1 \; if \;\; y_i^* > t \\ 0 \; if \;\; y_i^* \le t \end{Bmatrix} \tag{6}$$

Equation (6) says that the probability that a farmer who applied for production credit is denied is equal to the probability that the unobserved continuous latent variable is larger than a defined threshold (t). For simplicity, the threshold value is pegged at zero. Then, the probability that a farmer who applied for credit is denied is

$$\Pr(Y=1) = \Pr(y_i^* > 0) = \Pr(X_i^{'} b + e_i > 0) = \Pr(e_i - X_i^{'} b) = F(X_i^{'} b) \tag{7}$$

The empirical model for assessing the characteristics of credit constrained farmers is presented in equation (8)

$$Y_i = b_0 + \sum_{k=1}^{12} b_k X_{i,k} + e_i \tag{8}$$

X is a matrix of characteristics influencing credit constrained status of soybean farmers. The specific characteristics in model (4) are defined in table 1.

RESULTS

Characteristics of soybean farmers in the study area

The main characteristics of the respondents involved in this study are presented in table 2. Out of a total of 215 soybean farmers who applied for production credit, 49.30 percent were given (henceforth, referred to as unconstrained farmers) while the remaining 50.7% were denied (henceforth, referred to as constrained farmers). Comparatively, more of the unconstrained farmers had formal education, belonged to farmer based organizations, had acquired some training on soybean production, had access to credit information, made savings from their farm activities, had buyers for their produce, had access to market information and had formal contracts compared to their credit constrained counterparts. On the other hand, constrained farmers were relatively young, had smaller households and less farm experience than unconstrained farmers.

The statistics in the lower part of table 2 indicate that while the average yield per acre for credit constrained farmers was 12.1 bags, unconstrained farmers realized a yield of 15.7 bags.

Table 1 Description of Variables and a priori expectations

Variable	Description and measurement	*A priori* signs
Age	Age of respondent (years)	+/-
Household size	Count of people in household cooking from the same pot	+
Formal education	Dummy; 1 if farmer is formally educated; 0 otherwise	-
Experience in farming	Number of years respondent has been farming	-
Membership of FBO	Dummy; 1 if farmer belongs to farmer based organization; 0 otherwise	-
Training on soybean production	Dummy; 1 if farmer has obtained training on soybean production; 0 otherwise	-
Distance to financial institution	Distance (in km) from farmers residence to the financial institution	+
Savings from farm earnings	Dummy; 1 if farmer makes savings from farm activities; 0 otherwise	-
Formal contract	Dummy; 1 if farmer has a formal contract; 0 otherwise	-
Available buyer for produce	Dummy; 1 if farmer has a buyer for produce; 0 otherwise	-
Access to market information	Dummy; 1 if farmer has access to market information; 0 otherwise	-

Table 2. Descriptive Statistics of Variables used in models

		Constrained		***Unconstrained***		***All observations***	
Categorical variables		Freq.	%	Freq.	%	Freq.	%
Production Credit status		109	50.70	106	49.30		
Formal education		21	19.27	35	33.02	56	26.05
FBO membership		73	66.97	90	84.91	163	75.81
Training in soybean production		63	57.80	92	86.79	155	72.09
Access to credit information		34	31.19	47	44.34	81	37.67
Savings from farm activities		43	39.45	65	61.32	108	50.23
Formal contract		58	53.21	68	64.15	126	58.60
Buyer for farm produce		68	62.39	73	68.87	141	65.58
Access to market information		53	48.62	55	51.89	108	50.23
Continuous variables	***Unit***	***Mean***	***Std.***	***Mean***	***Std.***	***Mean***	***Std.***
Yield	Bags/acre	12.08	9.31	15.69	9.04	13.86	9.34
Age	Years	41.21	12.46	43.39	14.44	42.28	13.48
Household size	Counts	8.41	5.10	8.88	3.88	8.64	4.53
Farm experience	Years	11.76	10.34	17.02	11.78	14.35	11.35

Characteristics of credit constrained and unconstrained farmers

In order to describe credit constrained farmers, the probit model presented in equation (8) was estimated using the maximum likelihood method. The results are presented in table 3. The model contained twelve variables that characterize credit constraint status of soybean farmers. The pseudo R-squared, count R-squared and receiver operating characteristic (ROC) curve (see figure 1) all indicate a moderate goodness of fit of the probit model. The model makes about 71% correct predictions all the time, based on the count R-squared. The likelihood ratio Chi-squared test indicates that the selected variables jointly and significantly explain the constrained status of soybean farmers. In the ROC curve, the y-axis captures sensitivity, which measures the probability of making correct predictions of 1, while the x-axis captures 1-specificity. Specificity measures the probability of correctly predicting a zero (0). The farther away the ROC curve from the 45° line, the higher the predictive power of the model (which is measured by the area under the curve). A poor model has an area under the ROC curve of 0.5, while a perfect model has a value of 1. Based on figure 2, our model has a moderate predictive power, with an area under the ROC curve equaling 0.7927. Thus, the tradeoff our model makes in correctly and incorrectly predicting zeros and ones is greatly reduced.

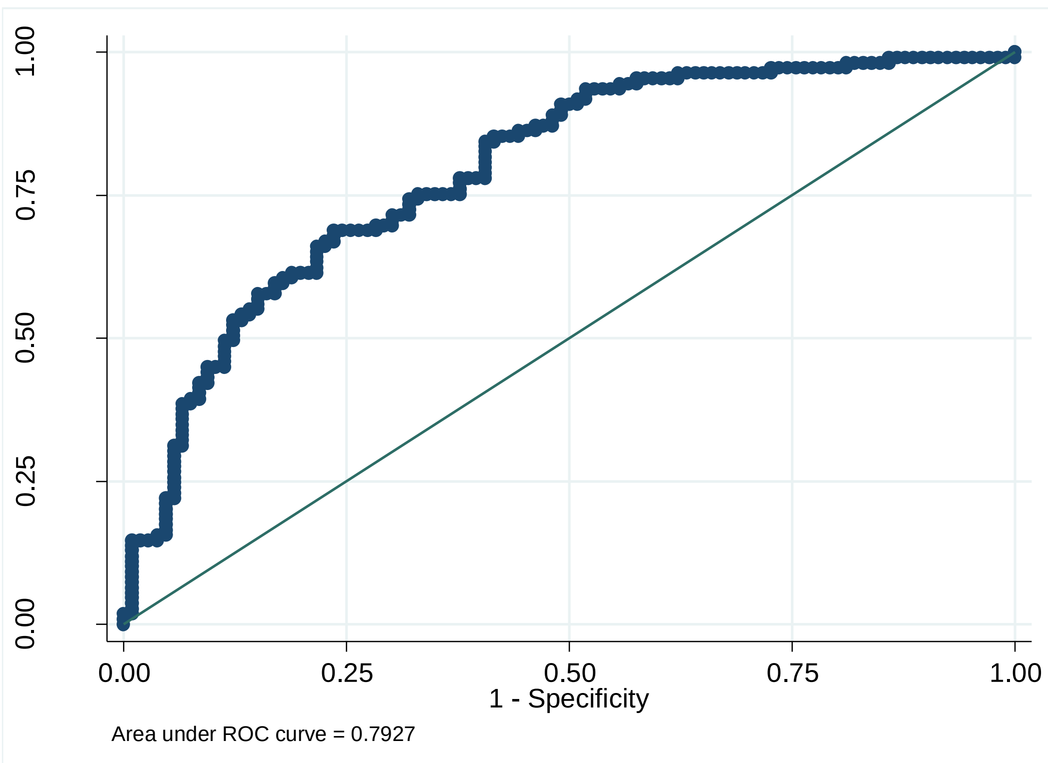

Figure 1: Receiver Operating Characteristic Curve to assess the goodness of fit of probit model

As expected, most of the anticipated signs of the characteristics were met, except household size, buyer availability and access to market information. Out of the 12 variables, 7 of them significantly influence the credit constraint status of soybean farmers. These include formal education, farm experience, FBO membership, training on soybean production, access to credit information, savings from farm activities and buyer availability. Characteristically, as indicated earlier credit constrained farmers are young, with small households, less experience, are non-members of FBO, have no training on soybean production, have no access to credit information, do not make savings from their farm activities and do not have ready buyers for their farm produce.

The results show that all other things being equal, formally educated farmers have about 21% chance of being granted a production credit from a financial or credit lending institution, while experienced farmers also have 1.02% higher chance of getting a production credit.

Table 3: Maximum likelihood coefficient estimates and marginal effects of the probit model

Variable	**Coeffient**	**Marginal effect (%)**
Age	-0.0019190	0.077
Household size	-0.0057498	0.229
Formal education	-0.5467992**	21.429**
Experience in farming	-0.0256240***	1.022***
Membership of FBO	-0.5630016**	21.853**
Training on soybean production	-0.8460441***	32.081***
Access to credit information	-0.3966926**	15.718**
Distance to financial institution	-0.0102160	0.407
Savings from farm earnings	-0.5467378***	21.535***
Formal contract	-0.1668278	6.642
Available buyer for produce	0.4529387*	17.899*
Access to market information	0.0941625	3.754
Model diagnostics		
Pseudo R-squared = 19.53%; Count R-squared = 70.70%; LR Chi-squared (12) = 58.20		
Prob > Chi-squared = 0.0000; Area under ROC curve = 0.7927; Number or observations = 215		

*, ** and *** indicate significance at 10%, 5% and 1% levels respectively

On the other hand, membership of FBO as well as access to credit information are important factors that facilitate non-refusal of production credit from lending agencies. Usually, farmers who belong to FBOs tend to have ready and easy access to information on production credit. Knowing more about the requirements, the do's and don'ts of credit facilities or lending agencies also enables the farmer to prepare and play cards that enhance the likelihood of being granted a loan.

Another important factor that lenders look out for is training on the business of choice, in this context training on soybean production. Training improves the knowledge of the farmer in terms of production practices regarding the crop so that the farmer is more likely to succeed than fail. Therefore, given two farmers with similar characteristics, the farmer who has had prior training on the enterprise of choice is about 32% more likely to get the credit applied than one without any training. It is satisfying to know that the training variable has the highest impact on the probability of credit constraint status of soybean farmers. The implication is that if any soybean farmer hopes to increase the chances of getting credit granted, it is advisable to obtain prior training on the enterprise.

The only counterintuitive result from this study has to do with the fact that farmers who have ready buyers for their produce are more likely to be denied of production credits. One would rather expect that credit lenders would want to deal with farmers with ready markets, but our findings imply the reverse. But a plausible explanation may be that the lenders may already have their own buyers where they can actually monitor sales and ensure loan repayment. Therefore, if a farmer already claims to have a ready buyer, their trust in them may be low, leading to their being denied of production credit.

Effect of credit constraint on crop yield

Before estimation using the PSM, the crop yield was naturally log transformed, so that coefficients could be interpreted directly in terms of percentages. The PSM estimation of credit constraint status on crop yield was done using three main matching algorithms, including the nearest neighbour (NNM), kernel based matching (KBM) and regression adjustment (RA), in order to compare the robustness of the estimates. Results are presented in Table 4. The ATE of soybean yield from the credit constrained farmers with NNM, KBM and RA were about 7.2%, 9.65% and 7.19% less than unconstrained farmers, respectively. All calculations were based on a 1-to-1 matching pairs, and were all significant at 1% level. This means that credit unconstrained farmers are significantly more productive than credit constrained farmers. For the constrained farmers alone, the impact of credit constraint, as measured by the ATT model are about 7.22%, 14.06% and 7.22% for the NNM, KBM and RA algorithms respectively. These significant values mean that, based on crop yield, the refusal of credit to some farmers actually impacts negatively on the productivity of farmers.

Table 4: PSM estimated of crop yield from soybean production

Model	NNM		KBM		RA	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ATE	-0.0720***	0.018	-0.0965***	0.034	0.0719***	0.018
ATT	-0.0722***	0.017	-0.1406**	0.058	-0.0722***	0.018
ATU	-0.0717***	0.019	-0.051**	0.021	-	-

Number of Observation = 215; ** and *** indicate significance at 5% and 1% respectively; NNM is nearest neighbour matching; KBM is kernel based matching; RA is regression adjustment

The estimates of ATE and ATT from NNM and RA models are approximately similar. According to Austin (2011), conditional upon negligible confounding if the marginal treatment effect (ATE) and the conditional treatment effect (ATT) coincide, then in our specific context, removing credit constraint from a population of soybean farmers would increase productivity by about 7.2%.

Balancing, Region of Common Support and Overlap Condition

In figure 2, we use the kernel-based density graph to test whether the overlap condition is violated or not. The overlap assumptionis said to be satisfied when there is a chance of seeing observations in both the control and the treatment group sat each combination of covariate values for credit constrained and unconstrained farmers. Evidence of violation of the overlap assumption is provided by the presence of too much mass around 0 or 1 for an estimated density(Busso et al., 2014).

The plot in figure 2 does not indicate too much mass near 0 or 1, and the two estimated densities for the unmatched sample have most of their respective masses at where they overlap each other. Thus, there is no evidence that the overlap assumption is violated. On the other hand, the graph in the right panel of figure 2 measures covariate balance in the matched sample between credit constrained and unconstrained farmers. For a balanced sample, we expect to see that the probability masses of the two densities perfectly overlap so that the constrained and unconstrained farmers become almost indistinguishable. The results clearly inidcate that samples were well balanced and their kernels perfectly overlap after matching. This means that after matching, constrained farmers become indistinguishable from the unconstrained counterparts based on the observable characteristics. Thus the findings based on the propensity score matching are accurate and relaible for further inference.

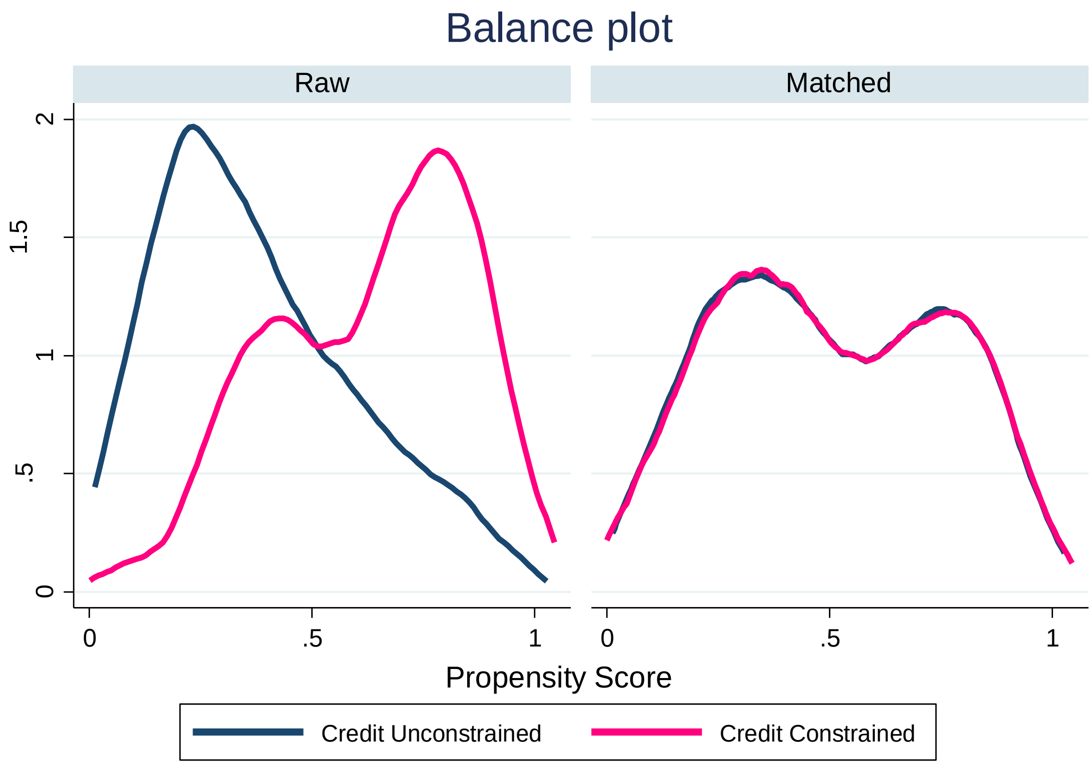

Figure 2: Propensity score distribution and region of common support for credit constrained and unconstrained soybean farmers

Again, we use the diagram in figure 3 to demonstrate the histogram of the region of common support for credit constrained and unconstrained farmers. Results are in conformity with the conclusions based on the kernel density balance plots. Most of the respondents in the matched sample are on the region of common support. A respondent on support means that the observation finds a suitable match, while observations that are off-support fail to find suitable matches. Based on figure 3, our matching exhibits a very good balance, and gives strong credence to the findings of significant producivity differences between credit constrained and unconstrained farmers.

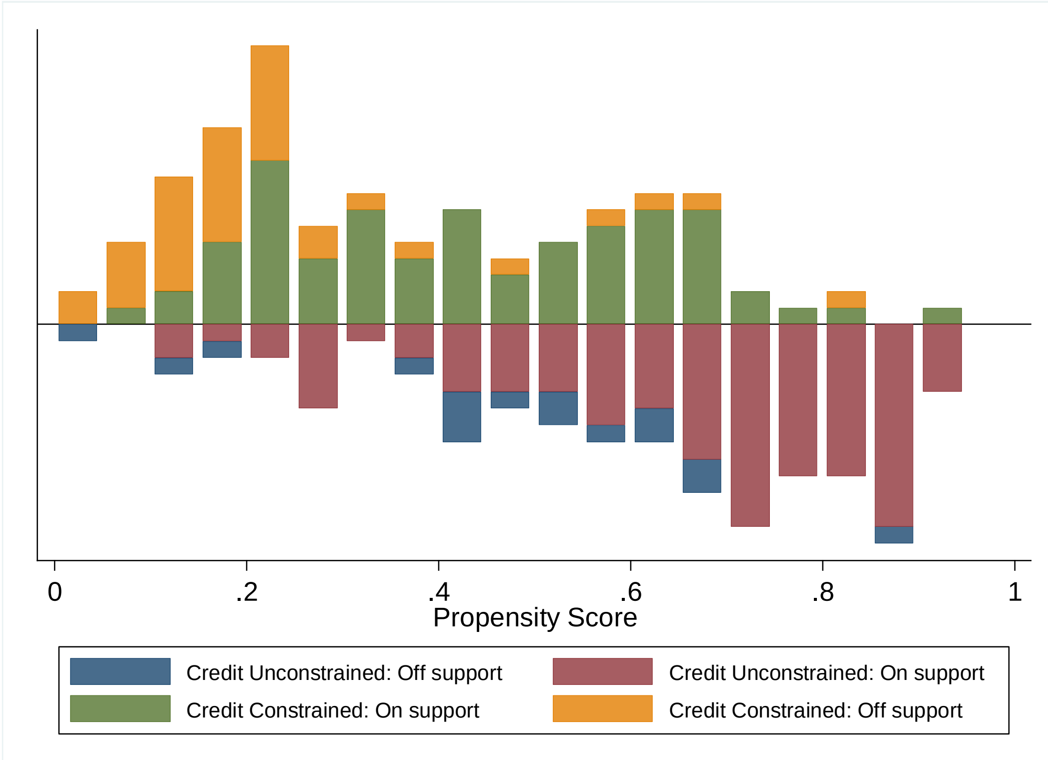

Figure 3: Propensity scores distribution and balancing on the common support condition

DISCUSSION

The impact of education on credit constraint status is very important because, all other things being equal, educated farmers are about 21% more likely to receive production credit they have applied than farmers without formal education. Education is essential because among other things, it is believed to improve the managerial capacity of farmers (Ansah and Tetteh, 2016). Financial institutions, both formal and non-formal are more interested in clients who can render a good deal in terms of repayment. They may know or believe that farmers with formal education are better able to manage the credit advanced so that they can easily repay. The implication, based on this finding is that formal education to farmers must be stepped up, if the ultimate aim is to reduce technical impediments of farmers accessing credit. The irony however, is that most of the farmers live in typical rural areas where access to education is itself a constraint. It is therefore not surprising that many of the less educated farmers are the people who find it difficult accessing production credit.

Farm experience is also an important factor that financial institutions consider before granting a loan or production credit. The finding of a negative effect of experience on credit constraint status is consistent with the studies done by Henning and Jordaan (2016), who concluded in a study of determinants of financial sustainability of farm credit applications, that experience and success factors were important in defining whether a farmer would be given a credit or not. Since farming is often a risky venture and subject to the vagaries of the weather, credit lenders tend to focus on people with more experience in their businesses, including farming. More experienced farmers might have ‘learnt from doing’ so that they become more resilient and poised to succeed even in the face of uncertain events. This increases their chances of

repayment, hence are more likely to be granted production credits once they apply.
In addition to education and experience, membership of FBO is also a prerequisite, or at least a factor that determines whether a farmer will be given credit or not. FBOs serve many important purposes. First, FBO membership enhances the social capital and networking skills of farmers. Second, lenders are usually more interested in working with farmer groups. Individuals in farmer groups can serve as guarantees for one another. Therefore, farmers who already belong to any farmer group of a sort have higher probability of being granted production credit. For this reason, many financial organizations and credit lending agencies prefer working with farmer groups. This finding confirms many empirical results (Dzadze et al., 2012, Denkyirah et al., 2016).
Training on soybean production is very important if current or prospective soybean farmers hope to apply for credit and be granted. The reason is that financial institutions or credit lenders are also profit oriented. Training is an important and informal way of acquiring knowledge and skills. While many smallholder farmers may not be educated, training on the enterprise of choice may provide a platform for farmers to be more competent. With enhanced competence, credit lending agencies may tend to be convinced of a positive outcome from the production process and therefore grant them the credit they apply.

The issues that constrain farmers from accessing credit from credit lending institutions have important implications for crop yield, and for that matter productivity. The ATE effect of credit constraint on crop yield indicate how influential lack of credit to support production activities could significantly reduce productivity. Farmers who were credit constrained were about 7% less productive that their unconstrained counterparts. Our findings are in conformity with the work of Awunyo-Vitor and Al-Hassan (2014), who also established a dampening effect of credit constraint on input use and maize productivity in the Brong-Ahafo region of Ghana. Policy-wise, credit constraint does not help to foster the national objective of increasing resource use and economic efficiencies, in that productivity is lower for farmers who are refused production credit.

CONCLUSIONS

The importance of credit availability to improve farm productivity has long been recognized, and our study provides evidence that supports this standpoint. Even though many farmers apply for production credit, a number of them are denied, and reasons for the denial are best known to the credit lenders or financial institutions. In this study, we tried to investigate the possible factors explaining why some farmers may be refused production credit while others are granted. Our findings are interesting and very conclusive. Farmers that are often denied production credit lack training on their micro-enterprises; they have little or no education and low level of farm experience. Also, such farmers do not belong to farmer groups, and for that matter they tend to have little or no information about production credit; they make no savings from their farm activities and already negotiate buyers for their produce.

RECOMMENDATIONS

Farmers can increase their likelihood of being granted production credits if they attend training sessions on their crop or livestock activities. Farmers without formal education may also have to enroll in education of some sort, be it formal or informal. Farmers would need to cultivate the habit of making savings from their farm activities. Policy-wise, since it is the objective of government to increase access to credit for smallholders, we propose two things. First, government can step up its extension services by designing customized extension services that focus on delivering intensive training on micro-enterprises of farmers, and possibly give such farmers certificates with which they can show as proof to financial institutions when they apply for credit. Second, government through extension agents can facilitate group membership and provision of credit information through such channels.

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