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Poverty targeting and income impact of subsidised credit on accessed households in the Northern Mountainous Region of Vietnam

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Abstract

This paper uses the data of 1338 rural households in the Northern Mountainous Region of Vietnam to examine the extent to which subsidised credit targets the poor and its impacts. Principal Component Analysis and Propensity Score Matching were used to evaluate the depth of outreach and the income impact of credit. To address the problem of model uncertainty, the approach of Bayesian Model Average applied to the probit model was used.

Results showed that subsidised credit successfully targeted the poor households with 24.10 % and 69.20 % of clients falling into the poorest group and the three bottom groups respectively. Moreover, those who received subsidised credit make up 83 % of ethnic minority households. These results indicate that governmental subsidies are necessary to reach the poor and low income households, who need capital but are normally bypassed by commercial banks.

Analyses also showed that ethnicity and age of household heads, number of helpers, savings, as well as how affected households are by shocks were all factors that further explained the probability at which subsidised credit has been assessed. Furthermore, recipients obtained a 2.61 % higher total income and a 5.93 % higher farm income compared to non-recipients. However, these small magnitudes of effects are statistically insignificant at a 5 % level. Although the subsidised credit is insufficient to significantly improve the income of the poor households, it possibly prevents these households of becoming even poorer.

Keywords: credit outreach, poverty reduction, subsidised credit, Northern Vietnam

1 Introduction

Poverty reduction is considered to be the main objective of anti-poverty programs including those targeting rural credit (Guirkinger & Boucher, 2008). Lack of access to credit is regarded as one of the most crucial reasons explaining why the poor rural households in developing countries remain poor (Collins *et al.*, 2009). However, providing credit to rural people, rural lenders have to deal with some risky issues such as rural seasonality, adverse selection, and higher transaction costs (Armendáriz & Morduch, 2010). Consequently, these issues create a trade-off between financial sustainability and depth of outreach (Cull *et al.*, 2011). Poverty targeting cannot be achieved by means of providing credit due to the pressure of financial sustainability by lenders (Hermes & Lensink, 2011). Focusing on sustainability can either ignore the provision of credit to the poorest households or eliminate the social goals of credit institutions. For this reason, subsidies might be necessary if

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credit institutions target the extremely poor but face the problem of financial sustainability.

In Vietnam, about 70 % of the total population lives in rural areas and 53.9 % of total national labour force works in the agricultural sector, which contributes nearly 22 % percent of total national domestic product. Moreover, nearly 94 % of the poor in Vietnam live in these rural areas. Most low-income households are rural households, which account for 44.8 % of total national households (General Statistics Office of Vietnam, 2012).

Vietnam has achieved significant success in poverty reduction in the last two decades. Poverty headcount rate reduced from nearly 60 % of the population in 1993 to 11.7 % in 2011. However, disparities in poverty reduction are still emerging. Poverty intensity is substantially higher in the Northern Mountainous Region. Although making up 28.79 % of natural area and 12.83 % of total population, the poverty rate is 60.1 % in the Northwest and 37.7 % in the Northeast of the country (Badiani *et al.*, 2012). Agricultural production serves as the main source of income for a high proportion of rural residents. Rice, maize and cassava are common crops and a variety of pigs, cows, buffaloes, chickens and ducks are kept as the main species of livestock.

The poor and ethnic minorities in the Northern upland region reported an especially high demand for credit. According to World Bank (2009), 81 % of the ethnic minorities see the capital shortage as a major constraint to investment in farming activities. In the region, poor households mainly borrow from the Vietnam Bank for Social Policy (VBSP) which was established in 2002 to provide the poor and ethnic minorities with subsidised credit. In 2011, VBSP, with the support of the United Nation Development Program (UNDP) and Vietnamese Committee for Ethnic Minorities (CEM), embarked on an expansion project set to be complete in 2020. The overall goal of this project is to reduce poverty through the expansion of the subsidised credit program. Specifically, the VBSP aims to achieve its goal of becoming a successful and sustainable Vietnamese microfinance institution by 2020. It is in this context that the poverty targeting and the role of subsidised credit in poverty reduction should be examined to provide information necessary on credit expansion and its relative success in alleviating poverty. This paper aims to answer two main research questions: (1) Does subsidised credit target poor households as a contribution to national rural development and poverty reduction? (2) Is the provision of subsidised credit an effective tool in improving household income?

2 Materials and methods

2.1 Data

Data used in this study are collected from the 2012 round of the Vietnam Access to Resources Household Survey (VARHS), which considered 3700 surveyed households in 12 provinces of the country. The VARHS 2012 survey covered a variety of topics relating to household endowments and access to resources. The survey was jointly conducted by the Institute for Policy and Strategy for Rural Development (ISPARD), the Central Institute for Economic Management (CIEM), and the Institute for Labour Science and Social Affairs (ILSSA) under the technical support from the Department of Economics at the University of Copenhagen. The survey was financed by the organisation of the Danish International Development Assistance (DANIDA). For the current work, data of 1338 households were extracted from four provinces, namely Lai Cai, Phu Tho, Lai Chau & Dien Bien in the Northern Mountainous Region of Vietnam. The existing data represent a practical, valid and useful source of information for this study.

2.2 Methods

2.2.1 Principal Component Analysis (PCA)

Meyer *et al.* (2000) defined the depth of poverty of clients targeted as how far down in the income distribution credit institutions can reach. This study focused on using a relative poverty index to evaluate the depth of outreach because it reflects the multi-dimensions of poverty and is less dependent on inflation rates over time (Zeller *et al.*, 2006). In order to compute a relative poverty index for each individual household, Principal Component Analysis (PCA) is used. PCA provides plausible and defensible weights for an index or assets to serve as a proxy for poverty. The main idea of PCA is to reduce the dimensionality of the dataset and define how the different indicators can be well combined to compute a relative poverty status of a particular household. Córdova (2009) suggests the use of the first Principal Component, which accounts for a highest eigenvalue of the correlation matrix of asset indicators. In this study, PCA is employed to extract a linear combination to best describe the indicators in a household dataset and transform them into one single index. The relative poverty index is measured as follows:

$$\text{Relative poverty score}_j = w_1H_1 + w_2H_2 + w_3H_3 + \cdots + w_nH_n \quad (1)$$

Where:
w_1, w_2, $w_3 \ldots w_n$ are the weights specified such that the poverty score index accounts for the maximum variances in H_1,H_2, $\ldots H_n$.

Because the original variables have very different measurements, they need to be standardised as follows:

$$H_n = \frac{h_n - \mu_n}{s_n} \tag{2}$$

In Formula 2, h_n is the value of the variable for each particular household, and μ_n and s_n are the mean and standard deviation of the variable for the whole dataset. A household with a lower relative poverty score is relatively poorer than one with a higher score. After computing the relative poverty score for each individual household, non-recipients are classified into 5 equal groups. The top fifth is called the "richest" group and the last fifth is called the "poorest" group; therefore, each quintile accounts for 20 % of total households. The cut-off scores for each quintile determine the border or the limits between poverty groups. Based on those scores, households with access to subsidised credit are then assigned into the five corresponding groups to compute the share of each accessed household group in total recipients. The differences in percentages of each relative poverty group between households with access to subsidised credit and those without imply the depth of outreach.

2.2.2 *Propensity Score Matching (PSM)*

2.2.2.1 *Main ideas of Propensity Score Matching*

The key assumption of PSM is that clients and non-clients with similar characteristics should also have the same outcomes except for accessing subsidised credit. The comparison between household groups with similar characteristics yields less biased estimation results compared to Ordinary Least Square estimation (Huber *et al.*, 2013). Also, the estimators by PSM are less sensitive to functional forms compared to regressions (Blundell & Dias, 2009). This approach is much more flexible for estimating the welfare impact of credit on multiple outcome variables of interest (Imbens & Rubin, 2015). PSM is an especially useful approach to address the selection bias, which occurs due to unobservable variables, which do not figure into the credit access model but still influence the household outcome (Caliendo & Kopeinig, 2008).

2.2.2.2 *Selection of covariates*

The first step in PSM is to explore factors explaining the difference in credit accessibility between households with access to subsidised credit and those without. A household might decide to apply for subsidised credit based on its projected benefits as well as costs. If the net benefit is positive, then the household might choose to borrow and vice versa. The net benefit can be denoted by LV_i, which is a latent variable reflecting the net benefit of using credit. LV_i is assumed to associate with a set of explanatory variables H_i, which refers to household endowments, $H_i = (H_{1i}, H_{2i}, \ldots, H_{ki})$. Mathematically, the relationship can be written as follows:

$$LV_i = H_i\beta_i + \varepsilon_i, \varepsilon_i \sim N(0, \sigma_i^2), \forall i = 1, 2, \ldots M \tag{3}$$

Of which, ε_i is an error term following the normal distribution and M is the number of households. However, in reality, LV_i is not observable. Only an indicator variable for taking subsidised credit is observable and defined as:

$$TL_i = \begin{cases} 1 : \text{if } LV_i \geq 0 \\ 0 : \text{otherwise} \end{cases} \tag{4}$$

Where:
TL_i denotes the credit status of the household. TL_i equals one if the household took subsidised credit in the previous 24 months and otherwise zero. Suppose that credit access status is explained by household endowments in terms of different capital.

$$\begin{aligned} TL_i = f(&\text{social capital, physical capital,} \\ &\text{human capital, financial capital)} \end{aligned} \tag{5}$$

Because TL_i is a binary dependent variable, the probit model is more appropriate in estimating the conditional probabilities of accessing credit based on household endowments (Bun, 2002). The key question related to the specification of the probit model, however, lies in the selection of suitable explanatory variables. This is also the most important statistical problem today in regression models (Breiman, 2001). This model uncertainty leads to unreliability in the magnitude of coefficients, standard errors and misleading interpretation of results.

To address the aforementioned problems, this study is based on the approach of Bayesian Model Average (BMA). This approach has a number of attractive features in addressing the uncertainty of model selection and make the inferences less risky than previous approaches (Hoeting *et al.*, 1999). The main advantage of BMA is that it relies on the support of a posterior probability to select an appropriate set of explanatory variables (Blattenberger *et al.*, 2013). In BMA analysis, the Bayesian Information Criterion approximation (BIC) is frequently used as criteria for selecting appropriate models. BMA chooses a model which the lowest

BIC value. By using Gibbs sampling to simulate data of latent variables, BIC can be applied directly to the probit regression. According to Albert & Chib (1993), the purpose of Gibbs sampling is to calculate posterior distribution of parameters, approximate the value of latent variable and incorporate those variables into the model to achieve better parameters. BMA averages many model specifications, especially ones with high posterior probabilities to address the problem of model uncertainty related to estimated parameters.

2.2.2.3 *Income impact estimation*

The second step of PSM is to compare the differences in means of welfare variables between recipients and non-recipients, who have similar characteristics except for credit access. The welfare impact is denoted by the Average Treatment Effects on the Treated (ATT) and expressed formally as:

$$ATT = E(\Delta \big| D=1) = E(Y^1 \big| D=1) - E(Y^0 \big| D=0) \quad (6)$$

Where:
$E(Y^1 \big| D=1)$ represents outcomes for recipients.
$E(Y^0 \big| D=0)$ represents the welfare for matched non-recipients.
The equation (6) allows extraction of the effect of credit on the households from the total effects estimated. In empirical estimation, each treated observation i is matched j control observations and their outcome y_0 are weighted by w. ATT is calculated as follows:

$$ATT = \frac{1}{n_1} \sum_{i \in (D=1)} \left[Y_{1,i} - \sum_j w(i,j)\, Y_{0,j} \right] \quad (7)$$

Where: n_1 is the number of recipients; $Y_{1,i}$ is the outcome for the recipient i; $Y_{0,j}$ is the outcome for the matched non-recipient j; and $w(i,j)$ are weights.

Propensity Score Matching with bootstrapping is appropriate to make the estimations less sensitive to generally infer the larger target population (Austin & Small, 2014). For this reason, this study is further interested in constructing the distribution for the ATT estimator. A bootstrap sample is a sample drawn using replacements from the original sample, such that the size of the bootstrap sample is equal to that of the original sample (Efron & Tibshirani, 1993). In this approach, the bootstrap in this present study is applied to the matched households.

One key issue in executing PSM is the choice of matching algorithm because there have been several types of matching. The Nearest Neighbour Matching is an algorithm in which the individual recipient is selected as a matching partner for a non-recipient that is closest in terms of propensity score. The matching replacement is employed because the average quality of matching will increase and the bias will decrease (Imbens & Rubin, 2015). The second approach is radius matching, in which each recipient is matched with a non-recipient that falls within a specified radius. The third approach, the Kernel matching, of which each recipient is matched with several non-recipients, with weights inversely proportion to the distance between accessed households and non-accessed ones (Imai *et al.*, 2010). And finally, the idea of stratification matching is to compare the outcomes within intervals or blocks of propensity scores. Their joint consideration of these four methods offers a way to assess the robustness of the estimates (Becker & Ichino, 2002).

3 Results

3.1 *Subsidised credit and characteristics*

The subsidised credit of the VBSP is the major form of government intervention on rural credit markets in Vietnam. Borrowers pay only part of the commercial interest rate, and the remainder is paid by the government. Among the 1338 households in the sample, 259 received subsidised credit, making up 19.36 %. Accessed households received a credit amount from 2 to 30 million VND with an average of 19 million VND per household. Subsidised credit has the average duration of nearly 48 months. The VBSP charges much lower interest rates (0.72 % per month) when compared to a market rate of 1.36 % per month by the Vietnam Bank for Agriculture and Rural Development.

Proper utilisation of the subsidised credit in the appropriate fields can yield high benefits for farmers. Most borrowers primarily use subsidised credit for financing farming activities, making up 40.15 % of total recipients. Poor households also use credit for other purposes, including asset purchase (20.08 %), food consumption (5.79 %), education (12.36 %), nonfarm (2.32 %) and other purposes (19.30 %). In general, the structure of credit use is appropriate to lending policies, which focus on farming activities.

3.2 *Poverty targeting of subsidised credit*

3.2.1 *Selection of variables for Principal Component Analysis*

In this study, income per capita is considered the benchmark poverty indicator because it represents a comprehensive measure of welfare at the household level in many cultures (Zeller *et al.*, 2006). Other variables in the household survey are selected partly based on the suggestions by Chen & Schreiner (2009) for a simple poverty scorecard for Vietnam. The variables contributing to the poverty score index in this study are also selected based on statistical analysis. Accordingly, the criteria for variable selection are based on the strength and significance of the correlation of each variable with the poverty benchmark indicator. Only those statistically correlated with the significance level of less than 1 % with the benchmark indicator are used in the Principal Component Analysis. Correlation of a binary variable with the benchmark indicator is calculated by the approach of Point-Biserial Correlation (Kornbrot, 2005).

3.2.2 *Results of Principal Component Analysis*

As discussed, only the first component, which has an eigenvalue greater than one and accounts for larger variance, is selected. Table 1 reveals the results of Principal Component Analysis. The table also reveals that all variables have a strong correlation with income per capita. Component loading coefficients represent the correlation between the variable and the first component. Most variables load quite strongly to the first component, as indicated by the absolute value of loadings. Only the first component has the best and strongest interrelationship with all different items, so it is the most appropriate component. When the value of a variable increases, with the exception of the variable family size, the household tends to be relatively wealthier.

The Kaiser-Meyer-Olkin (KMO) test is an index for comparing the magnitudes of observed correlation coefficients with the magnitudes of partial correlation coefficients. In this analysis, KMO equals 0.86, which is much greater than 0.60, indicating the adequacy of the sampling.

Table 1: *Results of Principal Component Analysis*

Variables and definition	*Mean*	*Standard deviation*	*Correlation coefficient*	*Factor loadings*
Income per capita (1000 VND)	12295.17	14401.62	1***	0.34
Age of household heads (years)	47.70	13.79	0.13***	0.14
Family size (persons)	4.94	2.06	–0.34***	–0.25
Square meters occupied by the household, including bedrooms, dining rooms, living rooms (m^2)	67.93	43.70	0.22***	0.17
Main construction material of the outside walls (1=cement, brick or marble/tile; 0= otherwise)	0.31	0.46	0.42***	0.41
Flooring material (1=cement, brick or marble/tile; 0=otherwise)	0.45	0.50	0.38***	0.37
Roof material (1= concrete/cement or tile; 0= otherwise)	0.32	0.47	0.30***	0.32
Households have electricity (1=Yes; 0=otherwise)	0.94	0.24	0.13***	0.13
Main source of energy for cooking in the household (1= Gas and electricity; 0= firewood or coal, etc.)	0.17	0.37	0.49***	0.36
Main source of cooking/drinking water in the household (1=Private tap water inside/outside the house, or purchased water in tank or bottle ; 0=otherwise)	0.05	0.23	0.25***	0.22
Type of toilet arrangement (1= flush toilet with specific tank and sewage pipes; 0= otherwise)	0.45	0.50	0.40***	0.36
Total asset (1000 VND)	14195.96	28859.23	0.43***	0.18
Model specification				
Eigen value				4.01
Variance explained (%)				33.43
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)				0.86
Number of observations				1338

*** significant at 1 % level, Note: sum of squares (Colum-loading) = 1

3.2.3 Poverty outreach of subsidised credit

This section relies on the relative poverty index calculated for each household to evaluate the poverty outreach of subsidised credit. Table 2 presents the poverty outreach of subsidised credit across relative poverty household groups. The table shows that the bottom three accessed household groups, especially the poorest, are overrepresented by subsidised credit when compared to non-clients. The shares of those households in total accessed households are greater than 20 %. The poverty target in the case of the VBSP is very consistent with its explicit mission to provide credit to the poor and low income households.

3.3 Income impact of subsidised credit on accessed households

3.3.1 Description of selected variables in explaining credit accessibility

It is assumed that credit access is not random, but rather conditional in accordance with household characteristics. There can be various household endowments influencing credit accessibility of poor households. In this study, the choice of relevant variables is based on literature review and potential significance for policy interventions (see Table 3 for further details).

HELP: Help is one important dimension of social capital. A better connection with helpers facilitates household social capital, which is necessary to overcome difficulties, access information, and improve the household economic situation (Story & Carpiano, 2015). Dufhues *et al.* (2011) indicate that greater social capital can improve the abilities of borrowers to repay these loans.

RELA: Behr *et al.* (2011) revealed that households with better relationships to local authorities might have better access to governmental credit programs. The coefficient sign of this variable is expected to be positive.

EXTE: Buadi *et al.* (2013) showed that households can manage and use resources effectively through access to agricultural extension services such as information support, input supply, and training. In addition, by maintaining relationships with agricultural extension stations, households can improve their social capital. It has conclusively been shown that social capital is very important in providing information on credit programs to potential borrowers and in reducing the cost of searching (Okten & Osili, 2004).

DIST: The distance of the household to the commune centre is used to capture household access to information as well as the costs of travelling to banks. A greater distance might hinder household social communication and increase transaction costs, which are expected to decrease the probability of credit access and repayment (Khoi *et al.*, 2013).

AGE: According to de Sherbinin *et al.* (2008), age of households can represent farming experience, which is relevant to productivity and efficiency of farming production. A younger household head could be more eager to adopt new technologies and therefore could have better credit access. Age also influences the household economic decision making regarding household consumption and production. In this sense, an older household head could have a better social reputation and a more cautious attitude about debt, which can also enhance credit repayment and credit access. There is an ambiguous relationship between age of household heads and credit access.

MINO: This variable captures the endowment differences between the ethnic minorities and the Kinh majority population in Vietnam. Ethnic minorities are expected to have better access to subsidised credit.

HSIZE: It has been suggested that a larger household with a greater number of labourers can have the potential to adopt farming technologies and generate greater profits (Nuryartono *et al.*, 2005). In addition, Yuan & Xu (2015) investigated that family size is principal determining factor of connecting social network and accessing informal credit. However, a larger household has more economic dependants, increasing the likelihood of using credit for consumption purposes. The sign of this variable is therefore ambiguous.

Table 2: *Depth of outreach by subsidised credit*

Depth of outreach	*Relative poverty groups classified by the relative poverty index (%)*					*Total*
	Poorest	*Less poor*	*Medium*	*Better off*	*Richest*	
Without access to subsidised credit (n = 1079)	20	20	20	20	20	100
Access to subsidised credit (n = 259)	24.10	23.70	21.40	19.50	11.30	100

Table 3: *Description of explanatory variables and expected signs with respect to subsidised credit accessibility*

Variables	*Type*	*Definition*	*Expected signs*
HELP	Continuous	The number of people known who could be asked for help (persons)	+
RELA	Binary	Households have members, relatives or friends holding office or other trusted position in the communes (1=Yes).	+
EXTE	Continuous	Number of contacts with agricultural extension in the last 12 months (number)	+
DIST	Continuous	The distance of the household to the commune centre (km)	–
AGE	Continuous	Age of household heads (years)	+/–
MINO	Binary	Ethnicity of household heads (1= ethnic minorities)	+
HSIZE	Continuous	Total members of the household (persons)	+/–
EDUA	Continuous	General education of household heads (years in school)	+
NFAM	Continuous	Share of nonfarm-nonwage income in total household income (%)	+
SAVE	Continuous	Total value of savings (VND 1000)	+/–
SHOC	Binary	Households experience any types of shocks (1= Yes)	–
LOSS	Continuous	Economic losses due to shocks (VND 1000)	–
ASET	Continuous	Total value of household asset (VND 1000)	+
PLOT	Continuous	The number of land plots household own (number)	+/–

EDUA: A number of authors have considered the effects of education of household heads on credit access. According to Foltz (2004), a household head with a higher level of education is believed to be a better manager regarding farm household decisions, performing better risk management and higher income generation. Moreover, education level also represents the potential to access information and to work in off-farm activities. From the point of view of lenders, more educated households are more creditworthy than less educated ones. In a study conducted by Brehanu & Fufa (2008), it was shown that education and training experiences of borrowers are positively correlated with farmer profits and abilities to repay.

NFAM: Stampini & Davis (2009) concluded that households engaging in off-farm labour activities spend significantly more on seeds, services, hired labour, and livestock inputs. Nonfarm income is therefore considered support for financing farming activities. Households with higher nonfarm income are more likely to access technologies and are less vulnerable to risks (Simtowe *et al.*, 2006).

SAVE: On the one hand, sufficient savings can serve as an insurance tool and a financial substitution source for credit. As a result, households with enough capital from savings or income, demand less credit (Dong *et al.*, 2012). On the other hand, households with insufficient savings to finance agricultural production can also apply loans to fulfil their capital shortage. The coefficient of this variable is expected to have an ambiguous sign.

SHOC and LOSS: Shocks regarding bad weather conditions can reduce farming productivity (Zeller *et al.*, 2000). The poor are also vulnerable to shocks from illness and death in the household as well as fluctuations in commodity prices. Consequently, lending to the agricultural sector and the poor is considered to be so risky that lenders are reluctant to grant loans to these groups. Moreover, economic losses due to shocks reduce household income and can often push rural households further into poverty.

ASET: This variable reflects the total value of household furniture, television, radios, vehicles and other moveable assets. An asset is believed to represent the relative wealth level of households, which determines their credit accessibility (Takahashi *et al.*, 2010).

PLOT: This variable indicates the number of land plots a household owns. A great number of plots with small sizes might indicate internal land fragmentation, which is believed to discourage mechanisation and intensive investment in farming activities (Van Dijk, 2003). A study by Manjunatha *et al.* (2013) concluded that land fragmentation is the main determinant of inefficiency of irrigated farms. As a consequence of land fragmentation, agricultural productivity and income cannot be improved. However, in a developing country like Vietnam, more land plots might also represent the wealth level of households, which could enhance their credit access. There is an ambiguous coefficient sign for this variable.

3.3.2 Endowment differences between households with access to subsidised credit and those without

The explanatory factors for the differences in accessing subsidised credit might include variations of household resources. For this reason, it is interesting to look first at the difference in selected explanatory variables between recipients and non-recipients.

Results in Table 4 indicate that the number of contacts with extension services, distance to the commune centre, and educational level of household heads are insignificantly different between recipients and non-recipients. Credit receiving households seem to know more people whom they can call upon for help and also tend to have better connections with local authorities through relatives, friends. Also family size is substantially higher for these households. Subsidised credit tends to serve households with younger heads and ethnic minority households. Households accessing subsidised credit tend to be more affected by shocks. Recipients of subsidised credit have a lower share of nonfarm income because most of those clients engage in farming production. In addition, borrowers of subsidised credit have a significantly lower value of savings and assets but own a higher number of land plots.

3.3.3 Determinants of accessing subsidised credit

Table 5 reports the probability of including each explanatory variable, expected value, and standard deviation of coefficients derived from the BMA analysis. For example, the probability of including the age of household heads is 83.5 %. To explain the credit accessibility, 43 different models have been selected, which the 5 best models having a cumulative posterior probability of 0.3618. A good model has a small value for the Bayesian information criterion (Claeskens & Jansen, 2015). As a result the model with a posterior probability of 0.139 is finally selected. The rate of correct classification in this model is estimated to be 80.49 %. These five explanatory variables are associated with subsidised credit accessibility at a 1 % level of statistical significance: The variable indicating number of helpers (HELP) is positively associated with credit access. A household with a higher level of social capital is more likely to access subsidised credit.

Table 4: *Descriptive statistics and difference in means of explanatory variables between recipients and non-recipients*

Variables	*All sample (n=1338)*	*Without access to subsidised credit (n=1079)*	*With access to subsidised credit (n=259)*	*t-test, Pearson χ^2 (Pr)*
HELP	3.42 (3.87)	3.31 (3.64)	3.87 (4.70)	–1.79 *
RELA	0.28 (0.45)	0.27 (0.44)	0.33 (0.47)	3.76 *
EXTE	1.38 (2.22)	1.39 (2.34)	1.35 (1.64)	0.24
DIST	3.78 (5.45)	3.74 (5.62)	3.94 (4.68)	–0.58
AGE	47.70 (13.79)	48.43 (13.93)	44.62 (12.73)	4.24 ***
MINO	0.70 (0.46)	0.67 (0.47)	0.83 (0.37)	25.27 ***
HSIZE	4.93 (2.06)	4.81 (2.09)	5.42 (1.84)	-4.64 ***
EDUA	8.96 (3.65)	8.99 (3.63)	8.83 (3.78)	0.62
NFAM	0.06 (0.18)	0.07 (0.19)	0.05 (0.15)	1.97 **
SAVE	9587.40 (34869.86)	10851.70 (37808.01)	4320.34 (17142.39)	4.16 ***
SHOC	0.71 (0.45)	0.52 (0.50)	0.77 (0.42)	16.65 ***
LOSS	4292.25 (9188.06)	4084.11 (9248.39)	5159.38 (8897.45)	–1.73 *
ASET	14690.20 (28729.03)	15391.01 (31355.58)	11770.64 (12591.49)	2.93 ***
PLOT	10.81 (4.15)	10.60 (4.30)	11.66 (3.33)	–4.31 ***

t-test used for continuous variables. Pearson χ^2 used for discrete variables.
* Significant at 10 %; ** Significant at 5 %; *** significant at 1 %
standard deviations in parentheses

Table 5: *Determinants of accessing subsidised credit*

Variables	*Probability of inclusion (%)*	*Expected value of coefficients*	*Standard deviation*	*Coefficient of the most appropriate probit model*	
Intercept	100	–1.645e+00	5.054e-01	–0.9125 ***	(–4.98)
HELP	36.6	1.601e-02	2.338e-02	0.0274 ***	(2.84)
RELA	9.5	3.056e-02	1.055e-01	–	
EXTE	0.0	0.000e+00	0.000e+00	–	
DIST	0.0	0.000e+00	0.000e+00	–	
AGE	83.5	–1.484e-02	8.459e-03	–0.0091 ***	(–2.92)
MINO	77.2	5.031e-01	3.294e-01	0.3277 ***	(3.22)
HSIZE	33.2	3.306e-02	5.191e-02	–	
EDUA	0.0	0.000e+00	0.000e+00	–	
NFAM	0.0	0.000e+00	0.000e+00	–	
SAVE	40.4	–4.830e-06	6.994e-06	–7.66e-06 ***	(–3.95)
SHOC	79.0	4.285e-01	2.740e-01	0.3554 ***	(4.12)
LOSS	0.0	0.000e+00	0.000e+00	–	
ASET	2.6	–1.715e-07	1.306e-06	–	
PLOT	0.0	0.000e+00	0.000e+00	–	
BIC				–8.335e+03	
Posterior probability				0.139	
Number of observations				1338	
LR $\chi^2(5)$				59.26	
Prob > χ^2				0.0000	
Pseudo R^2				0.0451	
Correctly classified (%)				80.49	

*** significant at 1 %. z statistics in parentheses

The variable AGE is found to have a negative coefficient. Perhaps younger household heads demonstrate active participation in local mass organisations such as women's unions or farmers' unions. The younger heads could be more active in obtaining information regarding credit sources, farming technologies, and markets as well. There are, however, other possible explanations, which are supported by Barslund & Tarp (2008). These authors argue that older household heads demand less credit because they are more settled and less likely to take on new and capital-demanding initiatives.

The variable indicating ethnicity (MINO) has a positive coefficient. If all other variables in the model are held constant, ethnic minorities are more likely to receive subsidised credit compared to the Kinh majority.

Amount of savings (SAVE) is negatively associated with access to subsidised credit. Holding all other independent variables constant, higher amount of savings decreases the probability of accessing subsidised credit. This result is likely to be related to the saving behaviour of households, especially the poor. Savings can increase as a result of less access to credit. Poor households need savings as a precautionary measure to mitigate shocks and to supplement investment as well.

The other statistically significant variable is the household exposure to shocks (SHOC). As expected, the coefficient of this variable is positive. Possibly, shock affected households access subsidised credit in order to mitigate the effects of these shocks.

3.3.4 Income difference between two household groups without matching

Among welfare indicators, income is widely used by previous studies such as Wetterberg (2007), Li *et al.* (2011), and Arouri *et al.* (2015). For this reason, this study focuses on measuring income changes to examine the effects of subsidised credit. Table 6 shows that, before matching, clients of subsidised credit have a significantly lower total income, and total nonfarm income. However, farm income is higher in the case of these clients. The explanatory factors for the income differences might include variations in the quality and quantity of household resources allocated for economic activities and different access to credit.

3.3.5 Income impact of subsidised credit after matching

Heinrich *et al.* (2010) indicated that the inclusion of covariates that do not influence credit access can worsen the common support problem or unnecessarily increase the variances of the estimates. For this reason, variables including ethnicity and age of household heads, number of helpers, savings and exposure to shocks selected by the Bayesian Model Average serve as covariates in the PSM model. The means of explanatory variables before and after matching are also tested to evaluate the quality of matching. After matching, the differences are no longer statistically significant. Matching helps reduce the mean of bias from 26.3 % to 2.1 %. PSM succeeds in balancing the characteristics between credit recipients and non-recipients. In order to separate the impact of subsidised credit, all recipients from other credit sources such as the Vietnam Bank for Agricuture and Rural Development, the People's Credit Funds and informal credit are excluded from the estimation. Using the propensity score estimated in the probit model, recipients are matched with non-recipients to estimate the income impact of credit. In order to make these findings less sensitive to the selection of different matching algorithms, coefficients of the robustness check are also reported. The matching algorithms used are nearest neighbour, radius with a caliper of 0.001, kernel using a Normal density and Stratification. Furthermore, standard errors estimated using bootstrap are also shown in Table 7.

Results show that there seems to be a positive effect of subsidised credit on total household income and total farm income, but negative impact on total nonfarm income. The sign and statistical insignificance of those coefficients found on total income and total farm income are very similar using different alternatives. However, the case of total nonfarm income is a nonrobust result because the signs and level of the coefficient remarkably changes in the estimation methods. The provision of subsidised credit has led to increase total income of recipients by 0.32 % to 7.19 % and increase the total farm income by 3.46 % to 10.99 %. However, the magnitude of those impacts is small and statistically insignificant at a 5 % level of statistical significance.

The limited income impact could be attributed to the fact that most poor households use subsidised credit to finance agricultural production, which is considered to be less profitable due to the risks. Simtowe *et al.* (2006) indicate that credit is useful only for households with access to remunerative businesses and investment opportunities. Moreover, a majority of borrowers of subsidised credit are ethnic minorities, who have more disadvantages compared to the Kinh majority in terms of socio-economic conditions (World Bank, 2009). A situation in which poorer households benefit less from accessing credit can also be found in Thailand, a neighbouring country to Vietnam. Coleman (2006) emphasised the positive impact of credit, but only for non-poor borrowers. Van Rooyen *et al.* (2012) also showed that small loans have higher probability of harming the poorest households in sub-Saharan Africa and credit interven-

Table 6: *Income difference between two groups without matching*

Outcome	*All sample (n=1338)*	*No access to subsidised credit (n=1079)*	*With access to subsidised credit (n=259)*	*t-test*
Total income (1000VND)	50946.87 (49862.03)	52332.54 (52487.03)	45174.12 (36493.93)	2.58***
Farm income (1000VND)	20134.97 (20932.03)	19875.30 (21860.09)	21216.78 (16506.22)	–1.09
Total nonfarm income (1000VND)	21474.40 (42135.37)	22595.70 (44447.43)	16803.06 (30309.68)	2.49**

The absolute value of standard deviation in parentheses
1000 VND ≈ 0.04 Euro

Table 7: *Income impact of subsidised credit*

Components	*Measurement unit*	*Nearest* neighbour	*Radius (0.001)*	*Kernel*	*Stratification*
Total income	1000VND	1058.56 (3472.62)	3042.28 (2766.69)	145.25 (2402.64)	229.04 (2520.74)
	% change of income	2.41	7.19	0.32	0.51
Total farm income	1000VND	2127.31 (1501.69)	1178.22 (1274.40)	709.55 (1123.15)	766.11 (1134.65)
	% change of income	10.99	5.53	3.46	3.74
Total nonfarm income	1000VND	–325.29 (2946.38)	2165.07 (2371.63)	–615.57 (2062.65)	–349.38 (2095.89)
	% change of income	–1.89	14.47	–3.52	–2.04
Number of matched treatment		259	247	259	259
Number of matched control		186	520	782	782

Each column reports the matching estimator with a different matching algorithm (1) nearest neighbour matching using 1 nearest neighbour (2) radius matching with a caliper of 0.001 (3) Kernel matching using Normal density function and (4) stratification matching
Bootstrapped clustered standard errors in parentheses
Coefficients are corrected by bootstrapping with 5000 replications
1000 VND ≈ 0.04 Euro

tion by itself seems to have no significant impact. In addition, lending procedures by subsidised credit are quite complicated and based on a top-down approach. The administrative planning of credit disbursement needs to be approved by the local authority and the subsidised bank. While rural households, especially the poor, need credit in a timely fashion before the start of production seasons, subsidised lending is also highly dependent on the availability of subsidised fund.

4 Discussion

The limited access to credit is regarded as the main source of poverty in the Northern Mountainous Region, where most of the rural poor, ethnic minorities live and draw their primary income from agriculture. The Vietnamese government established a special bank to provide subsidised credit to poor households and recently expanded credit disbursement as well. In order to design credit schemes for poor households in the region, it is essential to examine the extent to which subsidised credit reaches the poor and identify factors influencing household access to this source of credit. It is also necessary to know how subsidised credit affects household income.

Results indicate that subsidised credit successfully reached poor households as the majority of accessed households belong to the three bottom groups, especially the poorest one. The separation of subsidised credit from the banking system is helpful to the poor in terms of improving their credit access. In this sense, governmental subsidies are necessary.

The other finding from this analysis is the limited income impact of credit on poor households. Although subsidised credit has positive impacts on total household income and total farm income, the magnitudes are small and statistically insignificant. The findings in this analysis are quite different from those by Cuong (2008), who concluded that the subsidised credit program has a positive impact on poverty reduction at the national level. However, his findings also noted that 67.1 % of recipients are non-poor. The result in this study is in line with the finding of Hao (2005), who reported that the impact of subsidised credit on poverty reduction was too small given the high costs of providing credit to the poor. With regard to the Northern Mountainous Region of Vietnam, the small impact of subsidised credit indicates that a wide range of complementary services including market access, farming technologies, risk coping measures, and infrastructure improvement are also necessary to the poor. In fact, during the last two decades, despite overall impressive achievements of poverty reduction, the Northern Mountainous Region in general and ethnic minorities in particular experienced lower rates of poverty reduction compared to the reduction rates country wide.

The success of subsidised credit schemes is highly dependent on the specific regional context. Although there is evidence that the poor are well served by subsidised credit, the conditions under which subsidised credit is an effective tool in fighting poverty need further studies. This paper used cross-sectional data, which could not examine the income impact overtime.

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