Chapter 9

Village Funds, Education and Poverty Reduction in Thailand

Education is a crucial strategy in the fight against poverty. The purpose of this chapter is to evaluate the impact of the village funds on poverty reduction through education at the household level. With the limitations of the data, the propensity score matching technique is used to construct a pseudo panel data for analyzing the poverty status change.

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ABSTRACT

This paper aims to determine the impact of microcredit on poverty reduction through education. We created a pseudo panel data by matching data from Thailand's Socioeconomic Survey in 2009 and 2010. The study used Bivariate probit model to deal with the endogeniety problem. The results show that MVC has contributed to household expenditures for education. However, higher expenditures on education cannot help the poor to get out of poverty. It also found that increasing the number of motorcycles in a household is more important to getting out of poverty for a poor household.

Keywords: village fund, microcredit, education, poverty reduction, bivariate probit, propensity score matching

JEL classification: G21, I25, I32

9.1 Introduction

The linkages between education and poverty can be considered in two ways (Oxaal, 1997). First, education can be used as a poverty reduction strategy to enhance skills and productivity among poor households. Most of the research evidence has confirmed that households with a higher level of education are less likely to be poor (Bonal, 2007; Cremin and Nakabugo, 2012; Gounder and Xing, 2012). Second, poverty is a constraint to educational achievement. The Millennium Development Goals Report 2010 argued that the biggest obstacle to education is poverty. In addition, the report showed that the poorest 20 percent of the households have the least chance of getting an education. They are 3.5 times more likely to be out of school than the richest 20 percent of the households (United Nations, 2010b). Brown (2003) analyzed decision-making and education within resource-constrained households in rural China. He argued that children from households that are poor and credit constrained were much more likely to drop out of school. Therefore, the lack of credit is a major obstacle to financing educational investments for some of the poor.

In the Thai context, parents feel a great sense of responsibility to ensure that their children have a good start to life. They devote a share of their resources to ensure their children's future by investment in education. After the child finishes education, and hopefully finds a good job, they would be expected to care for their parents.

Table 9.1: Ratio of Monthly Household Expenditures on Education Per Total Consumption Expenditures

	Poor	Non-poor	Total
2006	5.03	5.82	5.77
2007	5.13	6.30	6.22
2008	5.29	6.42	6.35
2009	4.81	5.98	5.90
2010	4.57	5.51	5.45
Average	4.97	6.01	5.94

Although poor households are faced with resource constraints, the ratio of monthly household expenditures on education per total consumption expenditures shows not much difference between poor and non-poor households. Poor households have a monthly household expenditure on education average of 4.97 percent, while non-poor households have on average 6.01 percent (Table 9.1).

According to the National Educational Act of B.E. 2542, "*all Thai citizens have equal rights and opportunities to receive basic education provided by the State for the duration of at least 12 years*" (Ministry of Education, 1999). Further, in academic year 2009, the government introduced an extended project to provide 15 years of free education. In addition to tuition and school fees, other related expenses such as text books, uniforms, stationery and materials were given free of charge to 12 million students. The budget was 18,000 million baht for the first semester of 2009 (NESDB, 2010).

Even though government provides funding to cover basic education, in reality households often face more expenses related to education. Households also spend money for a variety of school activities including books, uniforms, school equipment, and transportation. In some cases, they pay for special learning courses or enroll their children in private schools where they pay tuition fees.

Table 9.2: Average Household Expenditure on Education from 2006 to 2010

Unit: baht per month

Education expense	2006	2007	2008	2009	2010
Tuition and school fees for public school	943	1,102	1,195	984	961
Tuition and school fees for private school	1,589	1,595	1,985	1,903	1,647
Text books , school equipments	243	254	280	196	172
Special learning courses	681	750	1,577	765	702
Other education expenses	124	159	183	110	117
Total	**3,580**	**3,860**	**5,219**	**3,958**	**3,600**

According to the Socioeconomic Survey (SES) from 2006 to 2010, an average of 49 percent of total households incurred educational expenses for such items as tuition fees, books and equipment, special learning courses, and other education costs. In 2006, households spent an average of 3,580 baht per month (Table 9.2). The highest costs were for tuition fees: an average of 1,589 and 943 baht per month for private school and public school, respectively. In 2010, after the government's policy to extend free education into 15 years and support other related expenses, households still had education expenses on average 3,600 baht per month.

For some of the poor families, parents may borrow to overcome budget constraints for education investment. Microcredit is an important source of credit for the poor. Some evidence from Grameen Bank indicated that microcredit provides small capital to poor households for investing in income-generating activities. This results in increased household income and should increase expenditure on household consumption, including children's education (Dowla, 2011). In thailand, the Microcredit for Village and Urban Community Fund (MVC or Village Funds) was introduced as a part of the Thai government's poverty alleviation policy in 2001. It allocated one million baht per village as a community fund for investment and consumption including education. Therefore, the purpose of this paper is to evaluate the impact of microcredit on poverty reduction through education. This paper uses data from the Thailand Socioeconomic Survey (SES) in 2009 and 2010 to construct pseudo panel data. Then, it uses Bivariate Probit model to consider the relationship between microcredit, education expenditure and poverty status change.

The following section contains literature reviews. Section 3 addresses empirical methodology, data and summary statistics will report in section 4. Section 5 provides our empirical results. Section 6 will discuss some important issues and conclusion.

9.2 Literature Review

Microcredit is an important source of credit for the poor in order to overcome the limitations of the financial constraint. A large number of empirical studies have shown the positive effects of microcredit on economic and social aspects. For example, microcredit can raise household income and reduce poverty (Berhane and Gardebroek, 2011; F. Nader, 2008; Khandker, 2001). It can improve consumption and social indicators such as women's empowerment, health and education (Coleman, 1999; Maldonado and González-Vega, 2008; Nader, 2008; Pitt, Khandker, and Cartwright, 2006)

Becchetti and Conzo (2010) review links between microcredit and child education through four channels. First, borrowers use loans in order to overcome the limitations of financial constraint. Second, loans assist consumption smoothing, children do not need to drop out of school and go to work. Third, microcredit is lending to the poor, especially women, who have relatively stronger preferences for education than men. Finally, microcredit builds up businesses or expands household production activity. The case of child labor, it may increase the opportunity cost of sending children to school. Islam and Choe (2009) examined the impact of access to microcredit on children's education in rural Bangladesh. The results show that household participation in a microcredit program increased child labor and reduced school enrolment. Microcredit increases demand for labor in household businesses set up with microcredit, especially in poor and less educated households.

Takahashi et al. (2010) using panel data from the Gresik district of Indonesia in 2007 and 2008, examined outreach performance and the welfare impact in the one year following loan disbursement. Their results show that the impact of microcredit on various household outcomes was generally statistically insignificant, except for sales of non-farm for the non poor and schooling expenditure for the poor. The poor benefited more from access to microcredit through increased investment in education for their children than the non-poor did. They argued that "there is great hope that the vicious circle of poverty will be broken over the course of generations through investment in schooling" (Takahashi et al., 2010, p. 153). Following this initiative, this paper aims to analyze the relationship between microcredit, education and poverty reduction.

Education is a crucial strategy in the fight against poverty. Previous studies on the link between education and poverty can be separated into two groups; macroeconomic and microeconomic. The macroeconomic usually focuses on economic growth and education through the theory of human capital (Becker, 1964). Microecoomic focuses on the cost and benefit of education. Education increases skills, productivity, employment opportunities, and raises income.

However, there is some debate on the relationship between education and poverty reduction. Wedgwood (2007) argued that the difference in quality of education between urban (wealthier) and rural (poorer) sectors affects school enrollment in higher levels. Rural poor have less access to education, thus it is hard to narrow inequality. A study in Latin America indicated the threshold required in order to escape the poverty trap was 12 years of schooling, which is equivalent to a secondary education (Bonal, 2007). People who pass this threshold will get a good job and high income, while those who cannot pass this threshold have to work harder for less money and continue poor.

9.3 Research Methodology

9.3.1 The Model

This paper used Bivariate Probit model because an independent variable, whether monthly household expenditure on education increased in 2010 $(\Delta education\_dum)$, may be influenced by the dependent variable, poverty status change, a poor household1 in 2009 turn to be non-poor in 2010 $(\Delta poverty\_dum)$. If true, it will cause recursion as well as endogeneity. To avoid the possibility of endogeneity it is safer to use Bivariate Probit model.

The participation in the microcredit program might have a positive effect on education expenditure. First, microcredit is concerned as a new source of credit for households. They can use credit for more investments and/or consumption. Second, microcredit has been aimed at women's empowerment. It will also have positive spillovers to children because women are likely to invest in children's education and health more than men (Pahl, 2008).

The Bivariate Probit model is mentioned along with the theory in Green (1998). It can be shown by two equation simultaneous model as follows:

$$\begin{aligned} y_1^* &= (MVC)\lambda + X_1\beta_1 + \varepsilon_1, \\ y_2^* &= X_2\beta_2 + \gamma y_1 + \varepsilon_2 \end{aligned} \qquad (9.1)$$

where y_1^* is the utility of increasing education expenditure and y_2^* denotes latent variable for poverty status change. Both y_1^* and y_2^* are depending on household's characteristics, *X*, and unobserved components, ε. When ε_1 and ε_2 are joint normal distributions with zero means, variances one and correlation ρ. *MVC* is Village Funds' participation. Then, the Bivariate Probit model specifies the observed outcomes can write as follows:

$$y_1 = \begin{cases} 1 & if \quad y_1^* > 0 \\ 0 & if \quad y_1^* \le 0 \end{cases} \quad \text{and} \quad y_2 = \begin{cases} 1 & if \quad y_2^* > 0 \\ 0 & if \quad y_2^* \le 0 \end{cases} \qquad (9.2)$$

where the dependent variables are binary outcomes which y_1 $(\Delta education\_dum)$ is equals to one for monthly household expenditure on education increase in 2010 and

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[1] Poor household means a household has average monthly consumption expenditure per capita which include food, beverages, tobacco and other good and services less than the poverty line (Appendix A)

otherwise it is zero. While y_2 ($\Delta poverty\_dum$) is equals to one if a household change poverty status from being poor in 2009 to non-poor in 2010, otherwise it is zero. This model will collapse to two separate Probit models for y_1 and y_2 when *rho* equal to zero (Cameron and Trivedi, 2009). We apply a maximum likelihood estimator with robust standard errors by using the Stata command *biprobit*.

9.3.2 Data and Summary Statistics

(a) Data Collection

The data used in this paper come from the Thailand's Socioeconomic Survey (SES) in 2009 and 2010, conducted by the National Statistical Office. The data were collected every month throughout the year in the form of questionnaires, consisting of a series of questions about household and individual family members. Individual information includes personal characteristics (e.g., age, gender, education, etc.), occupation and benefits from government programs. At the household level, the primary information includes household income (only SES 2009) and expenditure. The village fund's information, such as amount of loan, frequency of borrowing, and purpose of loan were also recorded. In addition, we consider a household which has an average monthly consumption expenditure per capita (including food, beverages, tobacco and other goods and services) under the poverty line[2] as a poor household. The household characteristics from SES are shown in Appendix D. The total number of observations from SES 2009 and 2010 were 41,296 and 41,850 households, respectively.

Since our focus is on poverty status change, we look at poor households in 2009 becoming non-poor in 2010. However the SES 2009 and 2010 data sets, which include useful information dealing with the village and urban community funds, are not panel data. Then, we tried to overcome this limitation by constructing a pseudo panel data set using the propensity score matching technique. In this paper, we use an algorithm developed by Becker and Ichino (2002). This estimate is then used to match treated and comparison households by creating blocks that contain households with similar propensity scores (balancing property). The model

[2] Poverty lines in 2009 and 2010 were quoted from the National Economic and Social Development Board of Thailand (NESDB) and the decomposition of the lines for a particular province was calculated (Appendix A)

also needs to test whether the treated and comparison households of each block have the same distribution of covariates, the means of each characteristic do not differ. The Logit estimators for the propensity score are shown in Appendix E.

The sample used in this paper includes of 2,079 poor households in 2009. For the purpose of this paper, we consider two groups of poor household which are borrower and non-borrower households. Out of the total poor households, 780 (37.5%) borrowed from the Village Fund and 1,299 (62.5%) did not borrow. Our objective was to match two households with the closest propensity score, one from poor household in 2009 (treated) and the other form both poor and non-poor households in 2010 (comparison)[3]. Data descriptions after matching are concluded in next section.

(b) Data Description

After matching data in those two years, we considered the poverty status change and found that 1,883 households turned to be non-poor in 2010, whereas 196 households were still poor in 2010. Summary statistics for all variables using the bivariate probit model are presented in Table 7.3. The poor that turned to be non-poor households have a higher average age and education level of the household head, moreover, higher average investment in education and more motorcycles than those who are still poor.

Table 9.3: Statistical Summary of Variables Using in the Model

Variables	**Turning to be non-poor in 2010**		**Still poor in 2010**	
	Mean	Std. Dev.	Mean	Std. Dev.
More education expenditure in 2010 (yes=1)	0.397	0.49	0.393	0.49
Borrow from VF in both years (yes=1)	0.371	0.48	0.418	0.49
Loan size borrowed from VF in 2009 (THB 1,000)	5.339	8.53	6.740	10.71
Age of household head in 2009	56.296	15.12	54.765	14.63

[3] We matched 780 poor borrower households in 2009 with 9,576 borrower households in 2010 (both poor and non-poor) and 1,299 poor non-borrower households in 2009 with 32,274 non-borrower households (both poor and non-poor)

Table 9.3 (Continued)

Variables	Turning to be non-poor in 2010		Still poor in 2010	
	Mean	Std. Dev.	Mean	Std. Dev.
Women household head in 2009 (yes=1)	0.285	0.45	0.311	0.46
Education of household head in 2009 (years)	4.602	1.94	4.582	1.99
Marriage of household head in 2009 (yes=1)	0.747	0.44	0.760	0.43
Household size in 2009 (persons)	4.442	1.79	4.582	1.69
Dependency ratio in 2009	0.559	0.31	0.493	0.29
More motorcycle in 2010 (yes=1)	0.379	0.49	0.270	0.45
Land tenure in 2009 (yes=1)	0.917	0.28	0.954	0.21
Rural household in 2009 (yes=1)	0.530	0.50	0.520	0.50
Total observations	1,883		196	

9.4 Results

The village fund participants in this study are separated into two variables: whether household borrowed from the Village Fund or had access to credit (Model 1) and the loan size (Model 2).

Bivariate Probit estimates using a maximum likelihood estimator to account for the potential endogeneity are presented in Table 9.4. The results indicate that participation in the village fund affected change in education expenditure. The results are significantly positive for the village fund participants, both in access to credit (dummy variables) and its loan size. It indicated that households who participated in the village fund are more likely to have education expenditures increase in 2010. In other words, they borrow to pay for the education of their children.

Now, we turn our attention to the determinants of the change of poverty status during 2009 and 2010. Only more education expenditure in 2010 (or the change in education expenditure) is assumed an endogenous variable. All other regressors are assumed exogenous, whereas a dummy variable for more motorcycles in 2010 is used as one controlled variable. The main results of more education expenditure on poverty status change were significantly negative in both specification models. Changes in monthly household expenditures on education had a lower probability to change a household's poverty status to non-poor.

Table 9.4: Bivariate Probit Analysis for Determinants of Poverty Reduction and Education Expenditures

Dependent variable	Model 1 *Δeducation _dum*	Model 1 *Δpoverty_ dum*	Model 2 *Δeducation _dum*	Model 2 *Δpoverty_ dum*
More education expenditure in 2010		-1.3218**		-1.6523***
		(0.605)		(0.380)
Borrow from VF in both years	0.1616**			
	(0.073)			
Loan size borrowed from VF in 2009 (THB 1,000)			0.0054*	
			(0.003)	
Age of household head in 2009	-0.0006	0.0013	-0.0008	0.0013
	(0.002)	(0.003)	(0.002)	(0.003)
Women household head in 2009	0.0150	-0.0969	0.0115	-0.0738
	(0.075)	(0.096)	(0.074)	(0.092)
Education of household head in 2009	-0.0181	0.0032	-0.0193	0.0015
	(0.017)	(0.021)	(0.016)	(0.019)
Marriage of household head in 2009	0.0601	-0.0474	0.0715	-0.0377
	(0.086)	(0.102)	(0.082)	(0.094)
Household size in 2009	-0.0963**	-0.0379*	-0.0933***	-0.0462**
	(0.017)	(0.023)	(0.016)	(0.021)
Dependency ratio in 2009	-0.2544**	0.1213	-0.2385**	0.0246***
	(0.112)	(0.206)	(0.115)	(0.192)
More motorcycle in 2010		0.1756**		0.1454*
		(0.081)		(0.080)
Land tenure in 2009	0.1240	-0.2453	0.1427	-0.2187
	(0.111)	(0.161)	(0.106)	(0.156)
Rural household in 2009	0.0318	0.0647	0.0451	0.0628
	(0.058)	(0.069)	(0.057)	(0.063)
Constant	0.1784	1.8081***	0.1744	1.8792
	(0.221)	(0.299)	(0.218)	(0.269)
rho		0.7624		0.9072
		(0.295)		(0.141)
Number of observations		2,079		2,079
Log pseudo likelihood		-2,010.35		-2,012.33
Wald chi2		125.75***		287.33***
Wald test of exogeneity: chi2 (1)		2.03		3.61*

Notes: Numbers in parenthesis indicate robust standard errors.
***, ** and * represent level of significance at 99%, 95% and 90%, respectively.

Surprisingly, while the more education expenditure dummy variable is significantly negative, the dummy for whether households had increased the number of motorcycles in 2010 is positive and significant in all models. This indicates that the households who had the number of motorcycles increase in 2010 were more likely to change poverty status to be non-poor, or help the poor in 2009 turn to be non-poor in 2010.

The wald test of exogeneity is significant in model 2. It suggests that endogeneity exists in the relationship between more education expenditure and poverty status change. Hence, a standard Probit regression is inappropriate to estimate the magnitude of the more education expenditure effect.

9.5 Discussion and Conclusion

Empirical evidences have shown that households participating in the Village Fund had a higher probability to spend on education. However, more education expenditure could not increase the probability to change the poverty status become non-poor. Instead, increasing the number of motorcycles in a household is more likely to help the household get out of poverty. In the short-term, the return on motorcycle investment is more than the return on education. A reason may be that education is a long-term investment. Investment in a motorcycle has an immediate impact on poverty reduction, at least within one year. Possessing a motorcycle plays an essential role in daily work and life as it provides mobility for rural people: this enables the poor to travel into the city at a quicker pace. They gain access to better employment opportunities and are more likely to obtain a high wage job (Gödecke and Waibel, 2011).

This study tries to construct pseudo panel data between poor household in 2009 with the similar household characteristics in 2010 by using propensity score matching techniques. Further research should be conducted on real panel data to determine if these results are consistent.