Does household credit to the poor benefit their child schooling? A case study of peri-urban areas of Ho Chi Minh City, Vietnam

Tinh Doan[*]
John Gibson[**]
Mark Holmes[***]

[*]Department of Economics, the University of Waikato, Hamilton, New Zealand
E-mail: ttd1@waikato.ac.nz. Phone: (64 7) 838 4466 Ext 6267
[**]Department of Economics, the University of Waikato, Hamilton, New Zealand
E-mail: jkgibson@waikato.ac.nz. Phone: (64 7) 838 4289
[***]Department of Economics, the University of Waikato, Hamilton, New Zealand
E-mail: holmesmj@waikato.ac.nz. Phone: (64 7) 838 4454

Abstract

This paper uses a novelty dataset of poor households in peri-urban areas in Vietnam to estimate impacts of small loans on child schooling. The Probit and Negative Binomial model estimates roughly indicate no strong evidence of the effect, especially of informal credit. Formal credit is likely to have positive impacts on child schooling, but its effect is not strong enough to be conclusive. The paper suggests that to obtain the target of sustainable poverty reduction, easing access to formal credit sources as well as exempting tuition and other school fees are necessary to keep poor children at schools longer.

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1. Introduction

It is widely recognized that human capital plays an important role in sustainable poverty reduction (Maldonado & Gonzalez-Vega, 2008; Maitra, 2003). However, the poor encounter two key development issues: income constraint and low education. These lead to a vicious cycle of poverty. Income constraint results in low education investment that leads to low education attainment. Then low education results in low productivity and thus low income. Today, child schooling therefore receives much attention in development strategies as a solution to breaking down the cycle of poverty and future development. However, education investment is not an easy task for many households in developing countries, especially the poor households. Demand for education relies on parents' motivation and sight, income constraint, and competing demands for children's time (Maldonado & Gonzalez-Vega, 2008). Under perfect financial markets, credit would be a tool to guarantee full investment in education. However, the underdevelopment of financial markets and income constraints are main reasons of deficient education for children in developing countries (Edmonds, 2006; Jacoby & Skoufias, 1997; Ranjan, 2001). Due to credit constraints, many households are not able to borrow or borrow inadequately so they may pull their children out of schools or ask their children to cut down studying time to work especially when households face adverse shocks (Kurosaki, 2002). On the other hand, access to credit may help households to smooth consumption without the need to cut child schooling. Moreover, in Vietnam during the economic transition cuts in public subsidies in education have pushed private education costs up, so households especially the poor need other external supports including credit sources. Therefore, the aim of this paper is to evaluate the impact of household credit on child schooling of the poor in peri-urban areas of Ho Chi Minh City, Vietnam by looking at whether borrowing households keep their children at schools longer than households without credit participation. The paper also examines whether the sources of credit and sex of children matter in child schooling.

The paper is organized as follows. The next section is the review of literature on credit impact on child schooling. In section 3, we discuss data and estimation methods. Estimation results are presented in section 4, and final section is for summary and conclusions.

2. Literature on credit impact on child schooling

Human capital accumulation is widely believed to play a very important role in poverty reduction. Human capital includes many factors of which education is one of the key elements of human capital formation. Enhancing education, especially education for the poor, is crucial in poverty reduction and sustainable poverty reduction. However, schooling achievement is affected by household preferences, income constraint, and competing demand for children's time which influence demand for child's education. Lending to the poor is believed a solution to break down the above mentioned vicious cycle. This section clarifies the question how household credit affects child schooling.

According to Aghion & Morduch (2005, p. 201), microcredit may affect households in two ways.[1] First, microcredit may enable households to earn more. Higher incomes push up consumption which increases the demand for health care and child schooling. The positive impact on children education can be explained in the following way: credit can be spent on schooling (school fees, books, materials, uniforms, other schooling expenditure) as well as on improving children nutrition and shortening sickness time by taking medicines promptly. As a result, such spending helps keep children at schools. Similarly, Maldonado and Gonzalez-Vega (2008, p. 2,441) classify this channel of effect as "positive" if

[1] Generally, loans to the poor are small so credit and microcredit is used interchangeably in this paper.

household credit helps increase income. The credit is believed to generate household income (positive impact) and then positively influence demand for education. They name this effect as an "income effect". Because education is a normal good, and so income elasticity of demand is positive, then once income increases the spending on education will increase. The increase in education will positively affect child schooling. Therefore, "accessing to financial services allows households to smooth their consumption in order to improve their decisions about children's education (Maldonado et al, 2002, p. 29).

Furthermore, it appears that there is a positive link between credit participation and child schooling. Inadequate schooling (or child labor) in developing countries is attributed to lack of access to credit (Dehejia & Gatti, 2002; Edmonds, 2006; Jacoby & Skoufias, 1997; Ranjan, 2001). Households facing adverse shocks and having insufficient access to credit may cut down child enrolment and education spending to reduce household expenditure and send children to work in order to smooth household consumption (Jacoby & Skoufias, 1997; Kurosaki, 2002). When households are able to borrow adequately, they may not need child labor, so children may stay at schools longer and the dropout rate is then lower for the credit participants. For example, according to CGAP,[2] in Bangladesh almost all girls in Grameen Bank customers have some years of schooling while that of non-borrowers is only 60 percent. For boys, 81 percent and 54 percent for client and non-client households respectively have some schooling. It also appears to be a large differential in the schooling between the two groups of households. Another observed effect is that the ratio of children aged 11-14 who can read, write and do arithmetic doubled from 12 percent in 1992 to 24 percent in 1995 for BRAC members, while that of the non-members increased slightly to 2

2 CGAP, What is the relationship between Microfinance and the Millennium Development Goals?. Available at http://www.cgap.org/portal/site/CGAP/menuitem

percent during the same period. Many other studies showed that enrolment rate is higher for microfinance clients' children, and there is significant improvement in children's years of schooling after joining microfinance programs (Barnes, 2001; Chen et al, 2001; Morduch, 1998; Pitt & Khandker, 1998).

The second way that microcredit may affect households is through an increase in household employment. This may generate household businesses and undermine children's schooling because children have to replace their mothers in caring for their younger siblings, or help their parents to do some other work like animal husbandry, housework, and farming. In these cases, children may encounter adverse effects on schooling. Children quit schools immediately or reduce time for schooling (time at schools and time for homework and extra classes). As a result, their academic performance gradually gets worse, and thus the children may repeat classes or even find discouraged to stay longer at schools and finally drop out of schools. In addition, poor households might pull children out of schools when they face adverse shocks as a strategy to cope with risks in order to increase income and smooth consumption (Jacoby & Skoufias, 1997; Kurosaki, 2002). Maldonado and Gonzalez-Vega (2008, p. 2,441) classify this propensity of effect as "negative" since child labor is used as a strategy to cope with adverse shocks. Maldonado and Gonzalez-Vega name the effect as "the risk-coping effect or child labor demand effect". Child labor and schooling are exclusive parents' decision at a time (Edmonds, 2006).

Moreover, loans to the poor often have higher interest rates (except preferred loans) and short-term repayment condition; they therefore require high returns to repay (high) interest rates in a short time. To obtain this goal, poor borrowers can reduce their business costs by using their own labors including children. Consequently, children from borrowing households may be pulled out of schools. Beegle et al (2004) in a study on Vietnam find that households who borrowed from higher interest rate sources are likely to have more child labor, and suggest that to increase child schooling it requires facilitating the access to credit.

Empirical studies on credit impacts on child schooling offer mixed evidence. Pitt and Khandker (1998) find that girl schooling increased when households borrowed from Gameen Bank, but when households borrowed from other microcredit programs the positive impact on girl schooling was not observed. The combination of credit and propaganda of children's education benefits in group meetings by Grameen Bank, not only microcredit itself, may account for the positive effect on children schooling. Mason and Rozelle (1998) claim that households may choose to send children to schools if the expected future benefits are higher than the estimated costs. Once households perceive the benefits or positive returns of education, they will invest more in children's education. In contrast, Hazarika and Sarangi (2008), in a study on rural Malawi, find that children are more likely to work rather than go to schools if their households have borrowed. In the same case of Bangladesh as Pitt and Khandker, Morduch (1998) finds no effect on child schooling. Similarly, Islam et al (2009) even detect significantly adverse impacts on child labor and schooling in the same country in South Asia.

3. Data and Analytical Framework

3.1. Data collection

A survey of 411 borrowing and non-borrowing households was conducted from March to May 2008 in peri-urban areas of District 9, Ho Chi Minh City (HCMC) Vietnam.[2] Since our focus is on microcredit impacts on poor households, our sample was selected from a list of poor households whose income per capita was below the HCMC overall poverty line of six million Vietnam Dong per year. We use two-step sampling, first selecting wards and then households. The number of successfully interviewed households accounts for 25% of the total number of poor households in each of the selected wards in the district.

The survey was designed to collect data on household demographic-economic indicators, commune/ward characteristics, education, health care expenditure and borrowing activities. We also utilized GPS receivers to collect data on locations of households and facilities which allow us to estimate distances from each household to facilities e.g. schools. The sample is likely to be representative for the poor group whose income per capita is below the poverty line in the district but neither for Ho Chi Minh City nor for Vietnam.

3.2 Analytical Frameworks

The most difficult part of evaluating impacts is to separate out the causal effect of credit from selection and reverse causation biases which are very common to nearly all statistical evaluations (Aghion & Morduch, 2005). One should ask whether the changes in outcomes are more significant than what would have happened without rocredit. If one sees that the longsighted and richer households have credit participation, one has to ask whether the credit really affects the households' child schooling, or the better-off school-motivated and/or richer parents simply have an easier access to credit. There is a presence of selection bias here if the households have better motivation to child schooling so they try to borrow to support their children's education. Therefore the motivation affects both credit participation and schooling outcomes. The selection bias exists so the inference of estimated impacts on outcomes would be misleading.

The existing literature pays much attention to the selection bias (e.g. non-random placement of credit programs and self-selection into credit participation by borrowers) and believes that the selection bias may cause overestimates in the impact (Amin et al, 2003; Coleman, 1999 & 2006; McKernan, 2002). For our sample, the non-random placement of credit borrowing may be not a serious case of worry because all the surveyed households in our sample whose income per capita under VND 6,000 thousand are eligible for preferred credits from government funds. However, the selection bias by self-selection into credit borrowing due to difference in child schooling motivation would still exist. The motivation is not measurable, but the bias can be reduced by controlling for household income and parents' education.

Some papers on schooling employ the 2SLS (e.g. Berman & Knowles, 1999; Maitra, 2003) to address selection and reverse causation biases. Demographic and educational characteristics of household head, jobs of heads, household composition, and physical characteristics of houses etc. are used as instruments. However, none of these studies applies the rigorous test for weak instruments suggested by Stock and Yogo (2002). Although these papers apply the test for endogeneity, the test is not able to ensure the instruments are good enough. Indeed using possible weak IVs can lead to upward biases and the estimates may be worse than OLS estimates. In IV model applications, testing weak instruments using MLE models is crucial (Murray, 2006). With our data availability, we do not have good instruments which affect credit participation but not child schooling so we only apply conventional probit and negative binomial (NB) models.[3]

Probit and Negative binomial model

We examine two outcomes of child schooling: current enrolment and education gap. Analysis of the current enrolment is conducted using standard probit model. However, one single indicator e.g. grade attainment or current enrolment does not reflect fully children's schooling because they do not indicate how well children did at schools or whether or not children are grade-repeated while education gap enables to do so. Education gap can avoid

[3] Some potential IVs such as distance to banks, pre-treatment income and asset are used to conduct weak IV test, and the test results for weak instruments would be provided upon request.

the situation that children are currently not enrolled due to holiday or just dropped out of schools, and it also represents how well kids did at schools. So the education gap may better reflect longer effect while the current enrolment maybe reflects immediate effect.

$$\text{Education gap} = \text{expected years of schooling} - \text{actual years of schooling}$$

$$\text{Expected years of schooling} = \begin{cases} 0 & \text{if age} \leq 6 \\ (\text{age} - 6) & \text{if } 6 < \text{age} \leq 18 \\ 12 & \text{if age} > 18 \end{cases}$$

Estimating education gap needs to check distribution of the dependent variable before choosing models. We only examine the effect for a group of children from 6 to 18 years old, so the education gap can take positive integers from 0 to 12, and thus the outcome of education gap is Poisson distributed, and count data model is appropriate.

The count data model was well established (e.g. Cameron & Trivedi, 1986; Greene, 2008; Hausman, Hall, & Griliches, 1984; Patil, 1970; Winkelmann, 2008, amongst the others). Tabulating the data on the outcome (Y) is a simple strategy to see outcome distribution. The larger is the mean, and the smaller will be the fraction of zeros. In contrast, the smaller is the mean, the higher is proportion of zeros, so zero observations are important feature of the count data (Cameron & Trivedi, 2009).

Equidispersion assumption, a key assumption, of the count data model means equality of mean and variance of Y. In reality, equidispersion is commonly violated because count data is often overdispersed (Cameron & Trivedi, 2009, p. 556), that is (conditional) variance exceeds the (conditional) mean. The presence of unobserved heterogeneity is one of the most common reasons. In this case, the distribution has a longer right tail and variance-mean ratio exceeds one. The Poisson model is as:

$$E(y|x) = \text{exponential}(x'\beta) = \exp(x'\beta)$$

We start considering the *basic Poisson Model* (Cameron and Trivedi, 1986), let Y_i denote the outcome (occurrences), $Y_i = 0, 1, 2, \ldots, N$

Let $y(t, t+\Delta t)$ denote the number of events/occurrences observed in the interval $(t, t+\Delta t)$. Then the number of occurrences in an interval of a given length is Poisson distributed with the probability density as follows:

$$\Pr(Y_i = y_i) = e^{-\lambda i}\lambda_i^{yi} / y_i! \quad (1) \qquad y_i = 0, 1, 2, \ldots \; i= 1, 2, 3, \ldots N$$

Conditional mean and variance of Y_i equal $\lambda_{i.}$ when we control for some exogenous variables $X_,$ the parameter λ_i is now specified to be as follows:

$$\lambda_i = \exp(X_i\beta) \qquad (2)$$

This model is based on two assumptions. *First*, events occur independently over time. This assumption is in reality violated, it is likely that there is the time dependence between the occurrences of successive events (Cameron & Trivedi, 1986, p. 31). For example, Pr(A goes shopping on Tuesday | A went shopping on Monday) ≠ Pr(A goes shopping on Tuesday | A did not go shopping on Monday). *Second,* the assumption of equality of conditional mean and variance is hard to meet and fails to account for the overdispersion which is very common in applied work.

Negative Binomial Models

The negative binomial model is alternative to Poisson models, it has *Gamma* distribution: $\lambda_i = \text{Gamma}(\phi_i, v_i)$ where ϕ is mean and v is a precision parameter.

$$E[\lambda_i]=\phi_i \text{ and } Var(\lambda_i) = [1/v_i].\phi^2{}_i$$

$$\Pr[Y_i = y_i] = \int \Pr[Y_i = y_i \mid \lambda_i] f(\lambda_i) d\lambda_i$$

With mean of dependent variable $E[Y_i] = \phi_i = \exp(X_i\beta)$, and $Var(Y_i) = \phi_i + (1/v_i).\phi^2_i = E[Y_i] + (1/v_i). (E[Y_i])^2 = E[Y_i] [1+ (1/v_i). (E[Y_i])]$

Because $\phi_i > 0$ and $v_i > 0$ then $Var(Y_i) > E(Y_i)$, and thus the model allows for overdispersion. There are two types of NB models, Negbin we (NB1 - a linear variance function) and Negbin II (NB2 - a version with quadratic variance).

NB1: $Var(Y_i)=(1+ \delta)E[Y_i]$ implies a constant variance-mean ratio i.e. $Var(Y_i)/E[Y_i]=(1+\delta)$

NB2: $Var(Y_i)= E[Y_i].(1+\alpha.E[Y_i])$ implies a linear variance-mean ratio i.e. $Var(Y_i)/E[Y_i]=1+\alpha.E[Y_i]$.

Test for Poisson models is based on tests for alpha $\alpha = 0$ against $\alpha \neq 0$ (the test is similar for delta δ in NB1). The Wald test is used to test the H_0: Poisson ($\mu_i= E[Y_i]$) against H_A: Negative binomial model with mean μ_i and variance ($\mu_i + \delta.\mu_i$) for NB1 or $\mu_i(1+\alpha.\mu_i)$ for NB2. These two different parameterizations (Poisson and NB) imply different assumptions about functional form of heteroscedasticity. In reality, the outcome distribution is commonly overdispersed so the second assumption of the Poisson model is violated. Therefore, the NB models are preferable to Poisson models. This is the case of our data on education gap where we have a mean of 1.222 and variance of 5.0867 (see Appendix 2).

4. Empirical results

4.1 Descriptive analysis

Unconditional mean differences in child schooling of age group ranged 6 to 18 between borrowers and non-borrowers are presented in Table 4.1. Roughly, children from borrowing households have better schooling (higher enrolment and lower education gap) than their non-borrowers' counterparts. However, the difference is insignificant. The differences between borrowers and non-borrowers' child schooling are also depicted in Figure 4.1 and Figure 4.2, the difference in current enrolment between the two groups is not very obvious while education gap widens as age increases. This is perceptible because education gap reflects longer-term investment in schooling, and higher education needs larger amounts of investment, but the poor in less developed countries are often both income-constrained and credit-constrained. Moreover, during the reforms in Vietnam, cuts in public subsidies for higher education, which produce skilled labors, have pushed private education costs up. These in turn changed premium for skilled labors (Cloutier, Cockburn & Decaluwe, 2008), the higher education costs more so it needs other external supports including credit sources.

4.2 Estimation results

Before providing interpretation, model specification selection will be discussed. Some studies show that expenditure per capita (a proxy for household permanent income) is a good predictor of child schooling in Vietnam (Beegle et al, 2004; Behrman & Knowles, 1999). Accordingly, we control for pre-treatment and asset as a proxy for household wealth which can be predictors of the schooling. Furthermore, controlling for these variables can reduce selection bias as suggested by Mosley (1997) and can avoid the problem of reverse causation bias if current income or expenditure is used. However, to check the robustness of credit participation's effect, we run the alternative model specifications as in Table 4.2a and 4.2b but with current *expenditure per capita* (We take the *pre-treatment income* and *assets* out), we observe indifference in coefficients of credit participation and remaining variables on the right hand side.

Negative Binomial model implementing strategies

As discussed earlier, we check the outcome distribution to specify models for our count data of education gap. Details of schooling outcome distribution are presented in Appendix

2. The mean is much smaller than variance so the distribution of education gap is over-dispersed and has a longer right tail. Intuitively, the negative binomial models (NB) seem to be appropriate in this case. To confirm this, we then run Poisson models and tested for overdispersion, all the test results are statistically significant regardless of different alternative specifications at the 1% level, so the Poisson regression models are strongly rejected, and the NB model is confirmed. Zero-inflated NB model would be also potentially applicable since our data also contains zeros, but there is only 6.4%, not so high to be called "excess zeros", so it is not necessary to use zero-inflated NB models.

Furthermore, Cameron & Trivedi (2009) argue that the overdispersion parameter can vary across individuals so some variables can affect the location and scale parameters of the distribution, they therefore suggest the *generalized NB* model which allows the different effects of different variables on the location and the scale of the distribution. In our case, we compare the regression statistics, e.g. Log pseudo likelihood, and see that both NB2 and generalized NB produced identical results. As a result, we only apply NB2 model in the current research.

In most cases in Table 4.2b, 4.3b, 4.4b, and Table 4.5, the Alpha (α) is significantly different from zero;[4] this implies that using NB2 improves the fit of the models. The NB standard errors are smaller than its counterpart (Poisson) standard errors. And it indicates efficiency gains due to using NB (a more appropriate estimator).

Now we turn to the estimation results. we start with estimates for child schooling of a group aged 6 to 18 using maximum likelihood Probit for current enrolment in Table 4.2a and maximum likelihood NB for education gap in Table 4.2b. We then consider whether the impacts for boys and girls are different (Table 4.3a and 4.3b). Next we examine the impacts

[4] Alpha can be interpreted as a measure of the variance of heterogeneity

of different sources of credit in Table 4.4a and table 4.4b. Finally we check whether or not the combination of credit with parental education (and with income) help child schooling.

In each model, we include all children aged 6 to 18 years old. There are potential sources of biases that are between-household selection (i.e. which households send children to school and/or their children do better at school), and within-household selection (i.e. which children are kept at school or receive more investment from their parents). The first problem can be addressed by controlling for household characteristics including household income, asset, parental education, credit participation, head's sex, number of children, distance to the nearest school, household residing locations. For the later source of bias, we control for child characteristics including child's sex, age, and birth order. Schooling performance by children within a household may be influenced by child's IQ and parents' motivation (Bowles & Gentis, 2002). These factors' effects can be captured by parental education and household income/asset. However, this leads to another potential problem that is unobserved determinants of schooling are correlated across children within households. This results in biased estimated standard errors (Deaton, 1997). To correct this, robust standard errors are estimated.

Estimates in Table 4.2a and Table 4.2b indicate the probability of current enrolment and education gap. They are not significantly influenced by credit participation, even somewhat adversely affected by small loans. This implies that schooling is a long term decision which is likely to be determined by household wealth indicators (proxied by income per capita, parents' education), number of children, children's characteristics (sex, age), distance to school, and community attributes. This finding is similar to Cameron and Heckman (1998), Carneiro and Heckman (2002) they show that long-term family factors rather than short-term credit constraints determine education outcomes. On the other hand, Doan and Gibson

(2009) find that education expenditure is positively influenced by credit participation amongst households who send their children to schools. It is likely that level of education expenditure is a current immediate choice while decision of sending children to schools and children's academic attainment needs longer term investments and affected by family background and economic conditions. This finding persists with Keane and Wolfin (2001), they argue that credit would have a greater effects on consumption and labor supply than school enrollment.

Microcredit or small loans are not an appropriate way of financing for education investment because we observe from field work that the loans of the poor in the areas are often very short-termed, one year or less, so they may affect level of education expenditure but do not affect schooling decisions. Even though, some households borrowed, they are still credit constrained because they were lent less than what they demanded. Their loans are deficient to finance long-term investments such as sending children to schools. Furthermore, households especially the poor are often credit constrained in developing countries (Conning & Udry, 2005) and are able to borrow small loans (more likely from informal credit providers) which may not suffice to finance education particularly larger lump sums of tuition and registration fees for new schooling years (Mason & Rozelle, 1998). As a result, the small loans may not influence current enrolment, longer term and bigger loans therefore are necessary to improve child enrolment and education gap. Our finding is similar to Morduch (1998) and Islam et al (2009), who show that child enrolment of the program households is worse than that of those in control group.

As previously discussed, higher schooling fees and foregone earnings of older children would change roles of credit participation. Figure 4.1, Table 4.2a, and 4.2b (coefficients of child's age and child's age squared) reveal that child schooling degrades as children get older (i.e. enrolment rate declines and education gap increases). Intuitively, we may think that the effects at upper levels of education would be higher than at lower levels. In order to examine the varying effects at different age groups, we run separate models for age groups: 6-14, and 15-18 for corresponding educational levels: primary & lower secondary school and high school level (Table 4.2a and 4.2b, column 2 and 3). Estimates show no evidence of significant impacts on enrolment rate at any level from 6 to 18 years old. This is the case of the education gap. This finding is consistent with the previous discussion on trivial roles of small loans for child schooling.

In addition, we detect that the poor households are budget constrained as the number of siblings adversely influences child schooling in both the probit and NB models. Similarly to the argument by Mason and Rozelle (1998), the poorer having lower income, may reluctantly pull their children out of schools. Households may send their older children aged 15 to 18 into workforce in order to support their younger and/or more potentially intelligent siblings when household do not have sufficient borrowing opportunities. The drop-out of schools seems to happen more to boys in the older group of 15 to 18 years old (see sex and age coefficients, Table 4.2a, column 3). This is likely due to their worse academic performance in schools relative to girls (Table 4.2b) and probably due to being less harmful for boys than girls if boys go out to work as teenagers. The households did not borrow adequately to support their children's schooling, so the competition of being sent to schools among children is evidenced. In other words, if the income and/or credit constraint was not present, investing in children's education would have been in full so child schooling outcomes would have been not impacted by household expenditure, number of siblings, and ages at teenager levels.

It is likely that in developing countries, parents are biased in favour of boys in human capital investment such as education. The literacy gender gaps are very high in all developing regions, whereas the gap almost disappears in developed countries (Wils & Goujon, 1998). One may stratify the sample into boy and girl groups and estimate two separate regressions. However, small subsamples may reduce statistical significance of estimates. we therefore apply an alternative approach to test the equality of credit variable coefficients between the two models. To do this, we include interactions between each variable with a dummy of child' sex (boy=1) as additional variables. When the child sex dummy takes value zero (i.e. girl), all the interaction term coefficients equal zero, so the non-interacted coefficients provide effects for the girl group. In contrast, when child sex equals one, the interacted term coefficients give boy-girl difference estimates. Table 4.3a and 4.3b represent the impacts of credit participation on female child schooling and the boy-girl difference in the impact. For whole sample, female children from borrowing households have 9% probability of current enrolment more than the same-sex children from non-borrowing households. However, the effects are statistically insignificant at conventional levels. The effect on girls' enrolment is in the similar direction, and their magnitude (about 5%) is smaller but statistically significant at the 5% level for the younger group of primary and lower secondary education.[5] The difference in effects between boys and girls is about -17% (i.e. the effect of credit participation on boy schooling is about -8% (adverse effect), due to -8%-9%= -17%), it is statistically significant especially for the younger group (Table 4.3a, column 2 and 4). For both whole and sub-sample, girls are better off, while boys are worse off from household credit participation. The NB model estimates (Table 4.3b) tell the same story of the effects by sex but the effects are

[5] Due to small subsample of group aged 15 to 18, decomposing into male and female group is too small to run regressions, so we do not run regressions for the older group.

statistically significant at younger group subsample. For whole sample, household credit participation leads to a decline of 0.26 points in education gap for girls but leads to an increase of 0.37 points [0.37=0.11-(-0.26)] in education gap for boys. Roughly, this finding implies that the effect is not homogenous across child sex, and girls benefit from household credit participation while the credit affects adversely on boys' schooling. The t-test is also applied to test the unconditional differences in enrolment and education gap between boys and girls aged 6 to 18 in order to re-confirm what we find under Probit and NB model, and the test results (statistically significant at 10% level) show that for both schooling indicators girls are better off than boys.

We do not observe any evidence of priority to boy schooling in the peri-urban areas. It seems that the better academic performances by girls keep them in schools and help girls to receive more investment from their parents. Moreover, in the peri-urban areas in South Vietnam the traditional viewpoint of "valuing boys above girls or preferring boys to girls" seems to be increasingly weakened today. Even though the effects are not very highly significant, what we find here is contrary to finding by Islam et al (2009) who find that microcredit adversely affects both boys and girls, and the negative impact is stronger for girls than boys in Bangladesh. And it is very much contrary to Pitt and Khandker (1998) those detect significant effects of microcredit on child education especially for boys.

Children from informal credit clients (higher borrowing costs, in our surveyed areas the informal interest-earned lenders charge about 11%/month) may have to leave schools or work since their parents might be too poor to afford schooling fees and also may need extra labor for making income (e.g. Beegle et al, 2004). Therefore we want to evaluate the effects of particular sources of credit to answer the question as of whether different sources of credit matter in the impact on child schooling in different ways. we stratify the borrowers into three groups: borrowing from informal credit, from both informal and formal sources, and from formal credit sources. The estimates (Table 4.4a and Table 4.4b) show that formal credit affects positively while informal credit affects adversely on children's enrolment and education gap, and the effects are stronger for high school group. We conduct the parameter test for the difference in coefficients between formal and informal credit, the difference is statistically significant at the conventional level for current enrolment (Table 4.4a). However, the difference mostly comes from the older group of high school children (both Table 4.4a and 4.4b). There is evidence that older children can participate in labor force. For example, Islam et al (2009) and Hazarika and Sarangi (2008) find that children of borrowers are more likely to work. Furthermore, the short-term small amounts of informal loans may not suffice greater schooling costs at higher educational levels. These lead to uselessness of informal credit in child schooling in comparison with formal credit.

We go a step further by examining whether combination of credit and education helps the poor. This is motivated by the existing literature showing that credit itself cannot help the poor well. For example, Pitt and Khandker (1998) find that girl schooling increased when households borrowed from Gameen Bank, but when households borrowed from other microcredit programs the positive impact on girl schooling was not observed. Intuitively, the combination of credit and propaganda of children's education benefits in the group meetings by Grameen Bank, but not only microcredit itself, may account for the positive effect on children schooling. In our context we do not see such sorts of combination even with government preferred loans. However, we believe that parental education may play a role in accelerating the effect of credit uses in child education because higher educated parents are often longsighted for their children's future livelihood. To check the effect, we use an interaction term between credit participation and highest parental education. The interaction term will capture the effect of parental education on child schooling within the borrowing group. Moreover, families with more educated parents may have higher incomes, and households with lower income among the poor may be too poor to send children to school while the less poor can afford if they have extra money from borrowing. Therefore, one may think that credit to the richer households in the poor group may have stronger effects on child schooling. For example, Berhman and Knowles (1999) find that in Vietnam some important policies such as free school tuition at primary schools, fee exemptions for the poor, similarly fee-regulated school system may weaken the association between income and schooling. However, tuition just accounts for one third of what households pay directly to schools and is much lower than households' total school-related expenditures. Richer households have greater school expenditures in part because they get higher quality schooling including extra classes/tutorials that may help improve child academic performance which keeps children at schools longer and lower school gap.

Therefore, we do use an alternative interaction term between credit and pre-treatment income per capita to test a hypothesis that among the borrowers, higher income households may enjoy greater impacts on child schooling. The estimates of the two interaction terms are presented in Table 4.5. The effects of the both interaction terms are statistically insignificant.[6] This means that amongst borrowing household children of the poor, the parental education and household income make no differences in their schooling. In other words, there is no accelerator of parental education and initial income amongst poor borrowers. However, it is noted that the mean of highest parental education of the poor is only 5.5 years, very low relative to general household parents in Vietnam, about 8.9 years of education (GSO, 2006) and benefits or returns of lower education attainment are very

[6] One would be suspicious about noisily measured income, but parental education is less problematically measured.

modest (see Doan & Gibson, 2009).[7] As a result, low education of the poor does not help much in child schooling, but our finding is not conclusive for general households.

5. Summary and conclusions

This study uses novelty data set collected in 2008 by the authors. The study looks at the impact of household credit including formal and informal credit sources to the poor in the peri-urban areas in Vietnam. Only 17% of the loans are spent on education, and the average loan size for education purposes (VND3,665 thousand, approximately USD220) is much smaller than the average loan size (VND7,494 thousand). Our estimates show that small loans to the poor have insignificant effects on child schooling. This finding is consistent with the relevant literature (e.g. Morduch, 1998; Manski, 1993; Kane, 1994); credit participation or credit constraints do not affect school attendance significantly. Moreover, the greater school expenditure may relate to obtaining higher quality schooling and academic performance by more extra classes which is influenced by household budget constraint (Dang, 2007). Intuitively, it is likely that households are budget constraint and credit still has a role to play in education investment. However, the government fixed tuition levels may weaken or undermine the effects of household credit on schooling.

The effect of credit participation is not identical between boy and girl schooling. Girls are more likely to stay longer at schools. The finding is quite contrary to the existing literature on difference in boy-girl schooling impacts in South Asia indicating that microcredit benefits boys more than girls (Pitt & Khandker, 1998) or affects girls more adversely than boys (Islam et al, 2009). Furthermore, there is no evidence that in the peri-urban areas the traditional view of “boys over girls” which is common in developing countries exists. Our estimates show that better schooling performance by girls helps them receive more

[7] This figure is estimated for general household head’s education, if highest parental education of either husband or wife is estimated the years of education would be higher.

investment from their parents. In addition, risky environment in peri-urban areas to female teenagers is likely to be a factor influencing parents' decision of sending girls to work, so girls are more likely to be better off than boys at the same ages.

Formal credit has brought beneficial effects to children while informal credit has failed to do so, and the difference in the impacts between two sorts of credit is significant and mainly comes from the older group aged 15-18. Both standard probit and NB model estimates reveal identical results. Consequently, to improve child schooling and poverty reduction in the long term needs to ease the formal credit constraint for the poor. It is likely that the poor those rely much upon the informal credit will end up household debts and pull their children out of schools. Unfortunately, we do not have data on child labor to confirm our finding. Consequently, the informal credit may exacerbate poverty in long term rather than help the poor out of poverty. The poor are both income and credit constrained so government interventions are needed such as facilitating credit access to the households in order to pay schooling fees as suggested by Caucutt and Lochner (2005). The current student loan policy in Vietnam would help the richer students because students from the poor are dropped out in early age education, so it is too late to help many youths from poor households. As a result, expanding opportunities for the poor households to borrow in order to pay early-childhood development program is vital to eliminate poverty sustainably. Providing subsidies to all children is impossible solution in Vietnam since it may pose burden on government budget. An alternative of targeting subsidies to low-income household children's schooling is more efficient. However, that the government has currently exempted tuition for the poor students is deficient due to the fact that tuition just accounts for a small fraction (less than one third) in total cost of children's education. Therefore, expanding preferred loans to the poor and/or exemption to other schooling costs such as textbooks, uniform, study material, school building etc is a further necessary policy to encourage poor children to schools and keep them in schools longer.

Finally, the most challenging issue in measuring the impact of microcredit is the sample selection bias that is almost encountered in non-experimental microcredit practices. Though our survey sample is designed with a randomly sampling procedure, estimated results and inferences from the survey data on households borrowing may be biased because of the nonrandomized credit placement, selection by credit staff, or because of self-selection into borrowing activities by borrowers. The biases may influence the child schooling rather than credit participation. Panel data or instrumental variable methods if a good instrument is available are solutions to the problem. Unfortunately, our data does not support these approaches. However, a sampling strategy of selecting quite homogenous households whose income per capita is below the poverty line of VND 6 million would reduce the possible bias. Apart from that, assume that borrowers those have better entrepreneurships and motivation to child education, and a longsighted perception about child education, may spend more on child schooling, so our estimates would be upward biased. If that is the case, the child schooling would be even more adversely affected by credit participation because almost all of our estimates of the effect are small, statistically insignificant and adverse (negative for enrolment and positive for education gap). In other words, the true effect magnitudes can be even lower than the estimated ones.

Table 4.1: Mean values of some key variables and *t*-values for equal means for the group of 6 to 18 years old children by borrowing status

Variables	Borrowers		Non-borrowers		*t*-value
	Mean	Std	Mean	Std	
Head's sex (male=1)	0.528	0.500	0.606	0.491	1.43
Parents' highest education (years)	5.551	3.333	5.452	3.585	0.26
Head married (yes=1)	0.723	0.448	0.730	0.446	0.16
Head's age (years)	50.501	13.762	57.625	15.300	4.30**
Household size (persons)	6.087	2.743	6.433	3.335	0.97
Younger siblings under 6 years (yes=1)	0.280	0.449	0.240	0.429	0.82
Children from 6 to 18 years old	1.942	0.963	2.096	1.187	1.22
Members from 18 to 60 years old	3.325	1.670	3.202	2.002	0.57
Members older than 60 (yes=1)	0.293	0.456	0.529	0.502	4.33**
Distance to nearest aged-range school	1.247	1.481	1.298	1.451	0.31
Child's sex (male=1)	0.451	0.498	0.5481	0.500	1.75+
Child's age (years)	12.823	3.708	13.096	3.693	0.67
Value of durable assets acquired over 24 months, land and house (in log)	13.149	1.180	12.702	1.929	2.25*
Pre-survey income per capita (in log)	8.115	0.234	8.102	0.389	0.32
Enrolment rate (children aged 6 to 18)	0.784	0.413	0.760	0.429	0.51
Education gap[(a)] (children aged 6 to 18)	1.061	2.216	1.346	2.392	1.10
Enrolment rate (children aged 6 to 14)	0.917	0.276	0.911	0.288	0.16
Education gap (children aged 6 to 14)	0.265	0.750	0.429	0.951	1.20
Enrolment rate (children aged 15 to 18)	0.577	0.496	0.583	0.498	0.08
Education gap (children aged 15 to 18)	2.289	3.028	2.417	3.052	0.25

Notes: t-value statistically significant at 10% (+), 5% (*), and 1% (**). ([a]) The education gap here is a *real* gap between the expected years of education *minus* the actual children's years of education.

Table 4.2a: Marginal effects of credit impact on current enrolment

Explanatory variables	Whole sample	Children aged 6-14	Children aged 15-18
Credit participation (yes=1)	-0.0032	-0.0139	0.0223
	(0.08)	(0.66)	(0.23)
Pre-treatment income capita in log	0.0575	0.0781	-0.1928
	(0.97)	(2.48)*	(1.30)
Pre-treatment asset in log	0.0127	0.0023	0.0066
	(1.03)	(0.42)	(0.19)
Highest parental education (years)	0.0256	0.0125	0.0424
	(4.08)**	(3.84)**	(2.96)**
Household head's sex (male=1)	0.0231	0.0042	0.0453
	(0.62)	(0.19)	(0.54)
Number of children from 6 to 18	-0.0656	-0.0303	-0.1343
	(3.71)**	(2.79)**	(3.31)**
Labor force[(a)]	-0.0061	-0.0000	0.0041
	(0.69)	(0.01)	(0.17)
Child's sex (male=1)	-0.0892	0.0052	-0.2940
	(2.53)*	(0.30)	(3.64)**
Firstborn child (yes =1)	0.0334	-0.0305	0.1980
	(0.87)	(1.19)	(2.30)*
Child's age	0.1801	0.0907	-0.1884
	(4.87)**	(2.76)**	(4.13)**
Child's age squared	-0.0090	-0.0044	
	(5.79)**	(2.71)**	
LT ward (rural)	0.0256	0.0266	0.0251
	(0.49)	(0.96)	(0.21)
LP ward (rural)	0.0412	0.0197	0.0229
	(0.75)	(0.68)	(0.15)
PB ward (urban)	0.1231	0.0421	0.3103
	(2.24)*	(1.72)+	(2.17)*
Distance to the nearest school[(b)]	-0.0019	-0.0138	0.0364
	(0.13)	(0.98)	(1.01)
Observations	483	286	197
Pseudo R-squared	0.30	0.24	0.22
Wald χ^2 (all coefficients=0)	111.31	37.17	50.18
Prob > χ^2	0.000	0.001	0.000
Predicted probabilities at x-bar	0.858	0.965	0.596

Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for whole sample; Column 2 is for a sub-sample of children 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children 15 to 18 (high school ages). [(a)]The number of household members aged 18 to 60 as a proxy for labor force. [(b)]The distance is regarded to ages at different educational levels e.g. it is the distance to the nearest primary school if $6 \leq$ age ≤ 10; the distance to the nearest lower secondary school if $11 \leq$ age ≤ 14; the distance to the nearest upper secondary or high school if $15 \leq$ age ≤ 18.

Table 4.2b: Negative Binomial Regression (NB2) of credit impact on education gap

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Credit participation (yes=1)	-0.0313	0.0290	0.0168
	(0.15)	(0.09)	(0.07)
Pre-treatment income capita in logarithm	-0.2516	-0.7769	0.2454
	(0.85)	(2.13)*	(0.71)
Pre-treatment asset in logarithm	-0.0763	-0.0907	-0.0350
	(1.20)	(1.02)	(0.49)
Highest parental education (years)	-0.0818	-0.1523	-0.0485
	(2.46)*	(2.50)*	(1.33)
Household head's sex (male=1)	-0.0348	-0.2499	0.1293
	(0.21)	(0.75)	(0.68)
Number of children from aged 6 to 18	0.2046	0.2772	0.2106
	(2.65)**	(1.75)+	(2.13)*
Labor force	0.0252	0.0427	-0.0317
	(0.50)	(0.52)	(0.60)
Child's sex (male=1)	0.4080	0.3439	0.4509
	(2.41)*	(1.18)	(2.20)*
Firstborn child (yes =1)	0.0351	0.1317	-0.1242
	(0.18)	(0.36)	(0.57)
Child's age	0.3411	0.2704	0.3566
	(9.17)**	(4.78)**	(3.09)**
LT ward (rural)	0.1036	0.0813	-0.0282
	(1.62)	(0.38)	(0.34)
LP ward (rural)	-0.4784	-1.2703	-0.1637
	(1.97)*	(3.05)**	(0.55)
PB ward (urban)	-0.6430	-1.1201	-0.0917
	(2.59)**	(3.34)**	(0.25)
Distance to the nearest school	-1.1115	-1.5309	-1.2794
	(2.99)**	(2.77)**	(3.14)**
Constant	-1.8093	3.9100	-6.6078
	(0.68)	(1.45)	(1.63)
Observations	483	286	197
Wald χ^2 (all coefficients=0)	222.96	79.24	40.79
Prob > χ^2	0.000	0.000	0.000
Alpha α[(a)]	1.3868	1.2798	1.2193
	(5.85)**	(1.91)+	(5.45)**

[(a)]The alpha parameter, highly significant, means that the Negative Binomial regression is an appropriate approach. Model in column 2, the test of α=0 is accepted at the 5% level, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimator are similar. Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for whole sample; Column 2 is for a sub-sample of children 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children 15 to 18 (high school ages).

Table 4.3a: Marginal effect of credit on child education by sex (Probit model)

Explanatory variables	Child aged 6-18		Child aged 6-14	
	Girl	Boy-girl difference[a]	Girl	Boy-girl difference[b]
Credit participation (yes=1)	0.0915	-0.1712	0.0496	-0.2276
	(1.41)	(1.93)+	(2.37)*	(3.54)**
Pre-treatment income capita in log	-0.0405	0.1207	0.0164	0.0201
	(0.57)	(1.11)	(1.33)	(1.16)
Pre-treatment asset in log	0.0458	-0.0562	0.0033	-0.0078
	(2.74)**	(2.53)*	(1.57)	(1.92)+
Highest parents' education	0.0300	-0.0069	0.0027	0.0036
	(3.76)**	(0.58)	(1.93)+	(1.48)
Household head's sex (male=1)	0.0473	-0.1011	0.0216	-0.1073
	(0.92)	(1.26)	(1.81)+	(2.42)*
Number of children from 6 to 18	-0.0366	-0.0593	-0.0030	-0.0128
	(1.60)	(1.72)+	(0.62)	(1.96)+
Labor force	-0.0115	0.0117	-0.0003	0.0005
	(0.92)	(0.69)	(0.19)	(0.19)
Firstborn child (yes=1)	0.0759	-0.0988	-0.0011	-0.0200
	(1.49)	(1.13)	(0.11)	(0.82)
Child's age	0.2117	-0.0642	0.0386	-0.0232
	(4.45)**	(0.92)	(3.35)**	(1.22)
Child's age squared	-0.0098	0.0018	-0.0018	0.0011
	(4.99)**	(0.63)	(3.19)**	(1.15)
TNPA ward (urban)		0.1632		0.0214
		(0.41)		(0.52)
LT ward (rural)	-0.0708	0.2299	-0.0873	0.0981
	(0.88)	(0.59)	(1.91)+	(0.89)
LP ward (rural)	-0.0108	0.2239	-0.0526	0.1071
	(0.14)	(0.53)	(1.99)*	(0.83)
PB ward (urban)	0.0792	0.1792	-0.0157	0.0417
	(1.14)	(0.60)	(0.74)	(0.97)
Distance to the nearest school	0.0091	-0.0214	0.0000	-0.0072
	(0.45)	(0.78)	(0.01)	(0.97)
Pseudo R-squared	0.35		0.39	
Wald χ^2 (all coefficients =0)	135.74		84.70	
Prob > χ^2	0.000		0.000	
Observations	483		286	

Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%. [(a)] & [(b)] are coefficients of interaction terms between the explanatory variables and child's sex dummy (boy =1)

Table 4.3b: Impact of credit participation on child education by sex (NB model)

Explanatory variables	Aged 6-18		Aged 6-14	
	Girl	Boy-girl difference[(a)]	Girl	Boy-girl difference[(b)]
Credit participation (yes=1)	-0.2616	0.3726	-0.7496	1.1840
	(0.93)	(0.94)	(1.64)+	(1.98)*
Pre-treatment income capita in log	-0.2196	0.0736	-0.7754	0.2298
	(0.49)	(0.12)	(1.04)	(0.26)
Pre-treatment asset in log	-0.2109	0.2057	-0.1121	0.1425
	(2.06)*	(1.69)+	(1.08)	(0.96)
Highest parent's education	-0.1419	0.1023	-0.2420	0.1681
	(3.14)**	(1.63)	(2.60)**	(1.36)
Household head's sex (male=1)	-0.1436	0.2616	-0.4496	0.5953
	(0.54)	(0.76)	(0.83)	(0.90)
Number of children from 6 to 18	0.1271	0.1454	-0.1596	0.6861
	(1.10)	(0.96)	(0.76)	(2.27)*
Labor force	0.0379	-0.0254	0.0363	0.0741
	(0.47)	(0.25)	(0.39)	(0.52)
Firstborn child (yes=1)	0.0245	0.0858	0.1971	-0.0872
	(0.08)	(0.21)	(0.41)	(0.13)
Child's age	0.3491	0.0024	0.3610	-0.1924
	(6.37)**	(0.03)	(3.25)**	(1.56)
TNPA ward (urban)		-3.3406		-3.6775
		(0.64)		(0.53)
LT ward (rural)	-0.0019	-4.2596	0.2177	-6.1350
	(0.01)	(0.82)	(0.31)	(0.90)
LP ward (rural)	-0.4783	-3.7312	-0.9363	-3.9187
	(1.24)	(0.71)	(1.55)	(0.56)
PB ward (urban)	-0.6674	-4.4900	-0.1950	-6.6575
	(1.57)	(0.86)	(0.26)	(0.95)
Distance to the nearest School	0.1700	-0.0995	0.1092	0.0144
	(1.33)	(0.67)	(0.31)	(0.04)
Constant		-0.1659		4.2791
		(0.04)		(0.73)
Alpha (α)	1.3918		0.6967	
	(5.96)**		(1.57)	
Wald χ^2 (all coefficients=0)	292.74		131.02	
Prob > χ^2	0.0000		0.0000	
Observations	483		286	

Robust z statistics in parentheses; + significant at 10%; * significant at 5%; and ** significant at 1%. [(a)] & [(b)] are coefficients of interaction terms between the explanatory variables and child's sex dummy (boy =1)

Table 4.4a: Marginal effects of credit impact on enrolment status by types of credit (probit model)

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Informal credit	-0.0639	-0.0002	-0.1461
	(1.25)	(0.01)	(1.19)
Both sources of credit	-0.0160	-0.0409	0.0037
	(0.33)	(1.33)	(0.03)
Formal credit	0.0637	-0.0121	**0.1959**
	(1.25)	(0.39)	**(1.70)+**
Pre-treatment income capita in log	0.0634	0.0767	-0.1633
	(1.10)	(2.72)**	(1.13)
Pre-treatment asset in log	0.0155	0.0020	0.0125
	(1.22)	(0.38)	(0.36)
Highest parental education	0.0240	0.0135	0.0417
	(3.98)**	(4.53)**	(2.98)**
Household head's sex (male=1)	0.0184	-0.0050	0.0339
	(0.50)	(0.26)	(0.39)
Number of children from 6 to 18	-0.0613	-0.0269	-0.1227
	(3.48)**	(2.65)**	(3.02)**
Labor force	-0.0080	0.0014	-0.0069
	(0.89)	(0.35)	(0.28)
Child's sex (boy=1)	-0.0898	0.0079	-0.2883
	(2.58)**	(0.46)	(3.53)**
First born child (yes=1)	0.0318	-0.0265	0.1842
	(0.84)	(1.12)	(2.11)*
Child's age	0.1774	0.0860	-0.1754
	(4.86)**	(2.82)**	(3.82)**
Child's age squared	-0.0088	-0.0041	
	(5.77)**	(2.76)**	
LT ward (rural)	-0.0012	-0.0144	0.0235
	(0.08)	(1.08)	(0.59)
LP ward (rural)	0.0413	0.0246	0.0605
	(0.80)	(0.94)	(0.50)
PB ward (urban)	0.0438	0.0199	0.0637
	(0.81)	(0.72)	(0.38)
Distance to the nearest school	0.1116	0.0362	0.2535
	(1.96)+	(1.48)	(1.68)+
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.019*	0.672	0.007**
Pseudo R-squared	0.31	0.25	0.25
Wald χ^2 (all coeffs=0)	110.89	47.94	57.79
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%

Table 4.4b: Negative Binomial Regression for credit impact on education gap by types of credit

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Informal credit	0.1006	-0.1181	0.2852
	(0.44)	(0.28)	(1.02)
Both sources of credit	0.0995	0.2099	0.1184
	(0.40)	(0.52)	(0.44)
Formal credit	-0.3411	0.0239	-0.3897
	(1.25)	(0.06)	(1.25)
Pre-treatment income capita in Log	-0.2835	-0.8128	0.1778
	(0.99)	(2.21)*	(0.53)
Pre-treatment asset in logarithm	-0.0797	-0.0842	-0.0353
	(1.27)	(0.90)	(0.52)
Highest parental education (years)	-0.0788	-0.1580	-0.0455
	(2.50)*	(2.58)*	(1.32)
Household head's sex (male=1)	0.0062	-0.2003	0.1571
	(0.04)	(0.61)	(0.79)
Number of children from aged 6 to 18	0.1995	0.2659	0.1920
	(2.58)**	(1.69)+	(1.97)*
Labor force	0.0281	0.0271	-0.0069
	(0.58)	(0.34)	(0.13)
Child's sex (boy=1)	0.4206	0.2950	0.4364
	(2.53)*	(1.04)	(2.17)*
First born (yes=1)	0.0496	0.1236	-0.0912
	(0.26)	(0.34)	(0.42)
Child's age	0.3346	0.2691	0.3016
	(9.06)**	(4.76)**	(2.62)**
LT ward (rural)	0.1098	0.1045	0.0169
	(1.70)+	(0.45)	(0.20)
LP ward (rural)	-0.5633	-1.2547	-0.2732
	(2.35)*	(3.16)**	(0.93)
PB ward (urban)	-0.6962	-1.1615	-0.2750
	(2.88)**	(3.45)**	(0.79)
Distance to the nearest school[(a)]	-1.0455	-1.4828	-1.1493
	(2.82)**	(2.65)**	(2.85)**
Constant	-1.4565	4.2060	-5.2948
	(0.57)	(1.50)	(1.35)
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.084+	0.730	0.035*
Alpha (α)	1.3488	1.2806	1.1611
	(5.8)**	(1.91)+	(5.3)**
Wald χ^2 (all coefficients=0)	231.47	88.34	50.89
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

Note: Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Model in column 2, the test of α=0 is accepted at 5%, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimator are similar.

Table 4.5: Effect of interaction terms of credit and parental education

Explanatory variables	dprobit model[a]	NB model
Credit participation (yes =1)	0.7214	-1.2088
	(0.55)	(0.27)
Pre-treatment income capita in logarithm	0.0891	-0.2832
	(1.13)	(0.81)
Pre-treatment asset in logarithm	0.0130	-0.0638
	(1.07)	(0.96)
Highest parental education	0.0228	-0.1475
	(2.00)*	(2.35)*
Credit participation*income per capita	-0.0674	0.0849
	(0.58)	(0.16)
Credit participation*highest parental	0.0035	0.0918
education	(0.26)	(1.26)
Household head's sex (male=1)	0.0246	-0.0377
	(0.66)	(0.22)
Number of children from aged 6 to 18	-0.0669	0.2130
	(3.71)**	(2.69)**
Labor force	-0.0058	0.0258
	(0.65)	(0.52)
Child's sex (male=1)	-0.0894	0.3966
	(2.54)*	(2.37)*
First born child (yes =1)	0.0351	0.0382
	(0.91)	(0.20)
Child's age	0.1809	0.3453
	(4.87)**	(9.50)**
Child's age squared	-0.0090	
	(5.79)**	
LT ward (rural)	0.0173	-0.4528
	(0.31)	(1.80)+
LP ward (rural)	0.0378	-0.6104
	(0.65)	(2.35)*
PB ward (urban)	0.1212	-1.1433
	(2.12)*	(3.29)**
Distance to the nearest school	-0.0010	0.1028
	(0.07)	(1.64)
Constant		-1.4549
		(0.50)
Observations	483	483
Wald χ^2 (all coefficients=0)	114.17	224.50
Prob > χ^2	0.0000	0.0000
Pseudo R-squared	0.30	
Alpha (α)		1.3849
		(5.9)**

Note: Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; [a] the dprobit model estimates marginal effects.

Figure 4.1: Enrolment rate by age and borrowing status

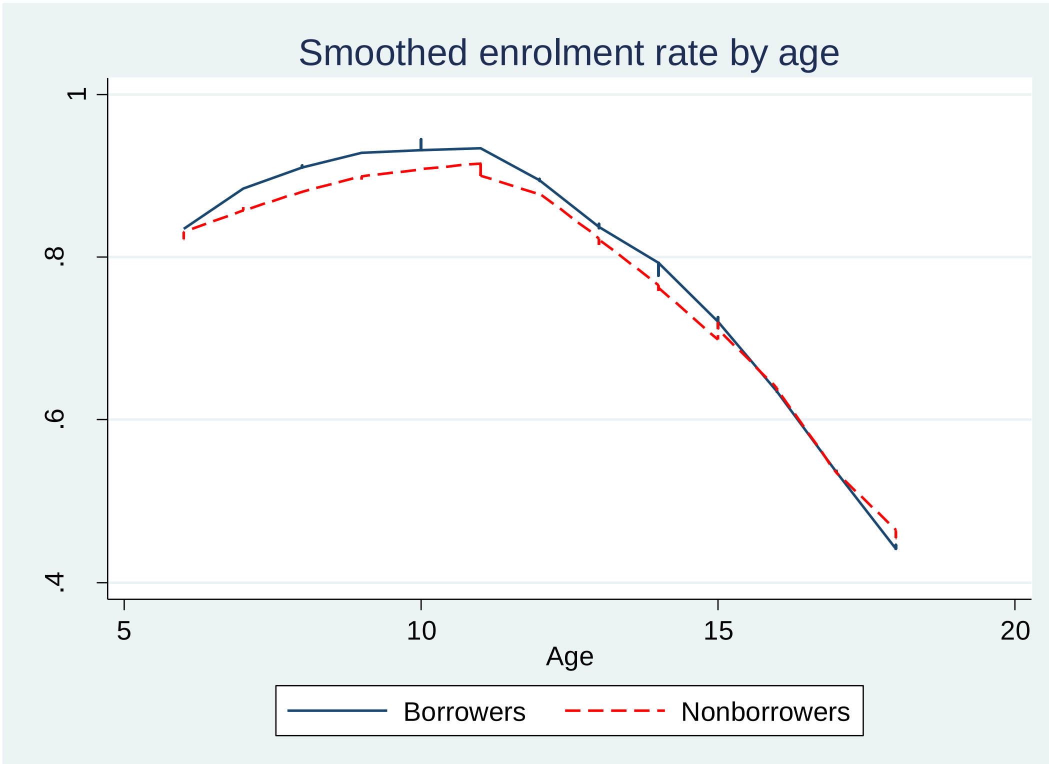
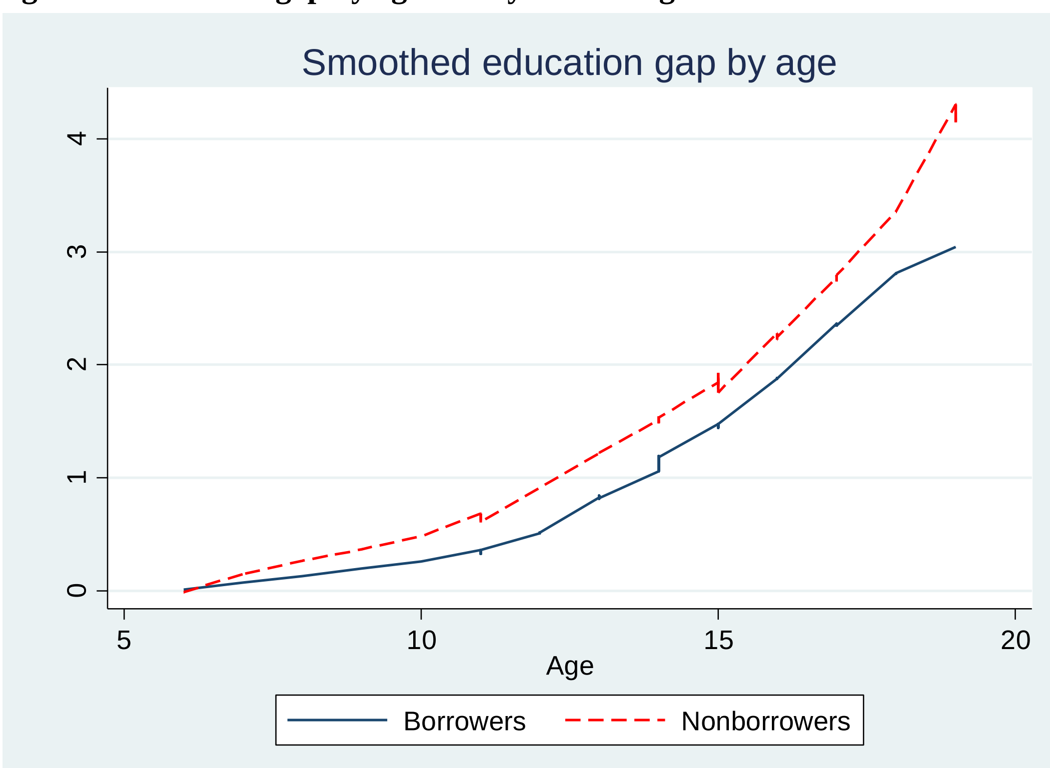


Figure 2: Education gap by age and by borrowing status



Appendix 1: Smoothed enrolment ratio and education gap by age for children aged 6 to 18

Child Age	Enrolment rate (%)		Education gap (years)	
	Borrowers	Non-borrowers	Borrowers	Non-borrowers
6	83.3	82.2	0.01	0.00
7	87.9	85.6	0.07	0.13
8	91.3	88.1	0.13	0.26
9	93.3	89.9	0.19	0.37
10	94.4	91.6	0.26	0.48
11	93.4	91.5	0.33	0.62
12	89.4	87.9	0.50	0.91
13	85.0	83.4	0.81	1.23
14	79.5	77.8	1.07	1.52
15	72.5	71.7	1.44	1.77
16	63.5	63.9	1.89	2.23
17	53.6	53.4	2.40	2.75
18	44.6	46.2	2.81	3.36

Notes: Bandwidth (a smoothing parameter) = 0.9 is chosen in the *Lowess* (locally weighted scatter-plot smoothing estimator) command in Stata®. This information is used to graph Figure 4.1 and Figure 4.2.

Appendix 2: Summary of education gap for children aged from 6 to 18

Variable	Observations	Mean	Variance	Std.Dev	Min	Max
Education gap	483	1.1222	5.0867	2.2554	0	12

Tabulation of education gap for children from 6 to 18 years old

Education gap	Frequency	Percent	Cumulative
0	31	6.42	6.42
1	284	58.80	65.22
2	64	13.25	78.47
3	32	6.63	85.09
4	17	3.52	88.61
5	14	2.90	91.51
6	8	1.66	93.17
7	12	2.48	95.65
8	4	0.83	96.48
9	1	0.21	96.69
10	8	1.66	98.34
11	3	0.62	98.96
12	5	1.04	100.00
Total	483	100.00	100.00

Source: Own estimation from author survey

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