Does microcredit influence parent's decision to send a child to school or to work? Evidence from Vietnamese rural households

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Abstract

Using three-year panel data drawn from the Vietnam Household Living Standard Surveys 2010, 2012 and 2014, this paper reports the results of a case study for rural Vietnam of the impact of microcredit on household decisions on child schooling and child labor. The analysis employs a number of instrumental variable methods featured in a random effects model, a generalized structural equation with first stage probit model, and a fully observed recursive mixed-process model in order to control for the possible endogeneity of credit and thereby identify the true effect of credit on the outcome variables. The analysis shows that credit participation by households encourages child labor and discourages child schooling in household that are recipients of microcredit. These findings raise a number of important policy issues. Microcredit programs are widely praised for their well-documented effect of raising household welfare and reducing household poverty, but what is generally ignored is the adverse effects of microcredit on child schooling and child labor. When introducing and evaluating of microcredit programs that target the poor in developing countries, the positive income effects of microcredit must be therefore weighed against the negative child labor effects.

Key words: microcredit, child schooling, child labor, poverty reduction, Asia, Vietnam.

JEL: H43, I21, I30, J13, O12

I. INTRODUCTION

Among several poverty targeting policies, microfinance has long been sought as an important instrument for poverty eradication through improving household welfare, which is generally measured in terms such as household expenditure and income, including income from self-employment[1]. Given the increased attention to microfinance and its role in reducing poverty, it is important to consider the effects of microcredit on household decision making beyond those that affect household income and expenditure. That is the aim of this study, which analyzes empirically the effect of microcredit on household decisions regarding child labor versus child schooling. A recent report by International Labor Organization estimates that 264 million children aged from 5 to 17 engage in economic activity in the world in 2012, which amount to 16.7 per cent of children in that age cohort, and most of them reside in low-income countries (ILO, 2013).

While definition of child labor varies in research and policy discussion[2], researchers often refer child labor as children involved in economic activities, either self-employed at home or working as hired labor in the market. There is wide consensus that child labor however defined is harmful to the physical and mental development of children and negatively interferes with their schooling, both in terms of attendance and performance. In addition, though child labor is not always a form of child abuse or child exploitation, especially when seen as a broad concept, it is a symptom of poverty (Edmonds and Pavcnik, 2005a). As such, child labor is deleterious to the well-being of children in a number of ways. Firstly, it limits children's current welfare as time spent working must trade off with other uses of child time such as leisure and schooling. Secondly, work participation prevents children from acquiring future education and denies them a wide range of benefits associated with education, which are vital to the process of human capital accumulation of the children. Finally, linked to household welfare, the practice of child labor may further trap poor households and their children in the cycle of poverty (Ljungqvist, 1993), or at least narrows the avenues of escape from poverty of poor households.

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[1] see Aghion and Morduch, 2005 chapter 8, Hermes and Lensink, 2007 for an intensive discussion on the impact of microfinance.

[2] According to the ILO's Statistical Information and Monitoring Program on Child Labor (SIMPOC) (ILO, 2012), a child is labelled as "laborer" when he/she works for wages (cash or in-kind); works in family farms or family enterprises for production or consumption purposes.

The focus on Vietnam is justified for at least two reasons. First, despite the importance of microcredit in Vietnam, and of the introduction of several microcredit schemes in recent years, there are just a few studies that have examined the impact of microcredit in Vietnam, and they merely focus on welfare outcomes of households (Lensink and Pham, 2012, Nguyen, 2008). Second, there is evidence that in the practice of child labor in Vietnam increased during the process of economic renovation (Edmonds and Turk, 2004, Edmonds, 2007), and of an intense participation by children in economic activities conducted at rural households in Vietnam (Edmonds & Pavnik, 2005b). Since these household activities are often selected as a primary target of various microcredit programs currently active in the country, it is likely that participation in microcredit programs has an effect on the incidence of child labor.

Drawing a three-year panel data from the most recent Vietnam household surveys 2010, 2012 and 2014, we estimate the impact of actual participation in a micro credit program, captured by both the dichotomous participation in microcredit programs and the actual loan uptake per household (or per head of households), on child schooling and child labor outcomes for rural Vietnam. The panel structure of the data allows us to use various instrumental variable methods, featured in wide range of models including a random effects model Baltagi-Chang generalized least squares, a generalized structural equation with first stage probit model, and a fully observed recursive mixed-process model. The presence of the microcredit program at the commune level and its interactions with household characteristics are used as instruments for credit participation in controlling for the endogeneity of microcredit.

The paper proceeds as follows. Section 2 lays out the theoretical background of the study and reviews the existing evidence of the linkage between credit and child labor. Section 3 describes our sample, followed by a descriptive analysis. Section 4 sets out our empirical model and discusses the estimation strategies that will be used. Section 5 presents the empirical results. Finally, section 6 concludes the paper.

II. ACCESS TO CREDIT, CHILD SCHOOLING AND LABOR

There is a growing body of research that is focused on determining the driving forces behind the prevalence of child labor, both from demand and supply sides. Much of the literature concerning supply-side effects considers child time allocation among its various possible uses and analyzes how returns and costs of schooling affect child labor. Thus, factors that raise the relative return to schooling may be expected to discourage child labor, whereas those that increase in return to child labor or in the parent's valuation of child labor may be expected to encourage child labor. Within this framework, credit market imperfections are derived as a cause of the incidence of child labor, among other economic and institutional factors.

There are a number of theoretical arguments as to how credit affects child labor and child schooling. One of the most solid arguments is offered by Baland and Robinson (2000), in which child labor is considered as a device for transferring income from the future to the present by credit constrained households. This occurs since putting children to work will raise current income while interfering with children development, and potentially lowering the future income. Removal of credit constraints will therefore allow households to borrow against future earnings, reducing the propensity of child work and lowering chance that children will be pulled out of school. This can be referred to as a risk management effect in that access to credit enables household consumption smoothing, and limiting households' exposure to income shocks. In a similar framework, Rajan (2001) also points to a negative linkage between credit and child labor, not due to risk management effect, but due to the welfare effect. In his model, poor families would have chosen to send their children to school if they had access to credit. So, by having credit constraint removed, households will enhance their allocation of resources to human capital investment, namely, schooling their children.

Alternatively, access to credit, and the use of credit tend to encourage child labor in other circumstances. Wydick (1999) considers the effect of credit on child labor in the context of home enterprises and suggests two opposing effects of credit. The "family-labor-substitution effect" occurs when working capital constraints are relaxed due to credit, and thus hired labor is substituted for child labor in the household. On the other hand, when credit is used to invest in physical capital or machinery, thereby enhancing labor productivity or the marginal return to child work, the 'household-enterprise-capitalization effect' takes place. If the latter effect dominates the former, a positive association between credit and child labor will emerges, that is children are more likely to be put to work. In this event, children will be scathed due to credit. So, while credit, especially microcredit may help improve household welfare through an initiation and/or expansion of self-employment activities, it is detrimental to the well-being of children in the households.

While theory is inconclusive on the linkage between credit and child labor, empirical evidence has also been mixed. At the country level, Dehejia and Gatti (2005) find evidence of a strong negative cross-country relationship between child labor and credit, which is measured by the ratio of private credit to GDP. At the household level, a growing number of empirical studies have been conducted to explore whether credit has an impact on child labor. Wydick (1999) examines the effects of microenterprise lending on child labor in Guatemala and finds that increased access to credit improves investment in child schooling as limiting the probability of children to work. However, the negative effect of credit on child labor is shown to be mitigated when hired labor is a poor substitute for child labor, or when credit helps to expand the business, and thereby raising the relative return to child work. A negative effect of credit on child labor is also confirmed by Ersado (2005) for rural Nepal and Zimbabwe, where access to credit, proxied by the presence of a commercial bank in the community, is reported to reduce child employment rates while raising school enrolment rate. A contrary finding is revealed for the Peruvian context in the same study, though. Chakrabarty (2015) discovers an interesting causal linkage between microcredit and child labor in a nexus with micro-insurance for Bangladesh and finds that for extremely poor households microcredit in combination with micro health insurance significantly reduce child labor. Other studies address child labor in conjunction with its reversed outcome, namely child schooling, discerning whether credit matters for improving schooling of children. For example, Maldonado and Gonzalez-Vega (2008) investigate the extent to which credit can help children stay long in school in Bolivia. In their study, credit is represented by membership in a microcredit program, and schooling gap is used as a measure for child schooling. The empirical analysis reveals that participation in microfinance programs matters for child schooling in that it narrows the schooling gap of children from households with affiliations to a microfinance institution as compared to that of children from households without microfinance's benefits.

In contrast to these common findings, a study by Hazarika and Sarangi (2008) built on the child-labor demand framework by Wydick (1999) reveals evidence that credit leads to an increase in child labor in household enterprises. Hazarika and Sarangi test the impact of access to credit, measured as a self-assessed credit limit, upon the propensity to work by children in rural Malawi. Considering both economic and domestic work that children may engage, their empirical analysis uncovers that credit raises the likelihood of child domestic work while having little effect on child economic work and on the school attendance of children. Based on this finding, the authors attribute an increase in domestic chores by children to a relief of adults' domestic burden as the latter takes up more economic work stimulated by an increased access to credit of the household. A very recent study by Islam and Choe (2013) discerns the impact of credit measured as a continuous treatment variable on child's education and child labor for rural Bangladesh, by carefully addressing the potential endogeneity of credit using instrumental variable for cross-section data. The study reveals evidence of an adverse impact on child's education among microcredit recipients as children are pulled off school in order to engage in work in household enterprise set up with support of microcredit. To some extent, the results of both above studies seem to challenge the effectiveness of microcredit programs as usually assumed in the literature on microfinance.

In the present study, we continue to question the role of microcredit toward child labor and child schooling for the case of Vietnam. Following Islam and Choe (2013) and Hazarika and Sarangi (2008), we hypothesize that a child-labor demand effect is likely to emerge given the intensity of children involvement in household income generation activities in rural Vietnam, combined with the absence/the failure of the rural labor market that limits the use of hired labor. Such conditions may allow credit to exert an adverse impact on child labor.

III. DATA

Data for this study are from the Vietnam Households Living Standard Surveys (VHLSS, henceforth) conducted in 2010, 2012 and 2014 by World Bank and the General Statistics Office of Vietnam. At the household level, the surveys provide a wide range of information on household characteristics, including basic demography, income, expenditure, and credit activities. At the individual level, information is available for demography, employment, education and health. The full sample of VHLSS 2010 covers 9,402 households with information on expenditure and income, of which 1,369 households borrowed from different sources of microcredit. Whereas, 1,175 households used microcredit among 9,399 households surveyed in 2012; and 3,675 households among 9,399 have participated in microcredit programs in 2014. We note that there are only 1,377 households in each year when linked as panel. It means that there are 4131 households in total three years. In order to construct a panel data set of the three year sample (2010, 2012, and 2014), we have identified a number of criteria in addition to household and individual identifiers. It means that the muddle of data processing will be solved strictly by the following matching step: (i) in each of year sample, we extract the zone of scanning data which includes the following norm identifiers: province, district, commune, area, household, member, relationship, year of birth, and gender; (ii) the three year sample will be merged by scanning these criteria simultaneously; and (iii) the merged zone will be loaded to each of the year to make the variables following the zone of identifiers, and then the constructed panel data will formed by adding together the three year sample.

Given our research objectives, we restrict our sample to rural households to include 1761 children aged from 6 to 15, as follows: (i) 589 children in the year of 2010; (ii) 596 children in the year of 2012; and (iii) 576 children in the year of 2014[3]. Credit data are confined to microcredit only, which is credit given by the Vietnam Bank for Social Policies (VBSP), whose primary objective is to ease the credit constraints of poor households and to provide them with procuring materials and agricultural inputs, other business and capital expenses, as well as means for partial payment of living expense. Although the VBSP is the major microcredit provider, another source of microcredit is from the Vietnam Bank for Agriculture and Rural Development, which also extends a wide variety of other loans than microcredit loans. The surveys, however, do not distinguish between loan types provided by this bank unfortunately[4].

The households in our sample that participated in the microcredit program provided by the VBSP consists of 104, 100 and 221 households, for the years 2010, 2012, and 2014 respectively. Credit information refers to whether a household participated in the microcredit program, and the total accumulated amount of credit received by households during several years preceding the survey year.

[3] We considered the unbalanced data that modifies each group of children aged from 6 to 15 in each year of data sample. The reason is that we try to capture as many as possible the number of children in each time of period within the merged sample of the three years.

[4] It is necessary to elaborate on our deliberate emphasis on microcredit from one Vietnamese bank. First, the VBSP microcredit program under study is the largest in the country in terms of both its outreach and the credit volume distributed per loan. Second, the program offers the most typical features of a generally defined microcredit program, namely the exclusive target on the poor, the operation under a group lending mechanism, and the provision of training and technical advice as a by-product of microfinance. Finally, most informal credit extended to rural households is for consumption purposes and thus its contribution to employment activities of households is limited.

We construct two measures for child schooling, namely current school attendance dummy[5] and schooling gap. The first variable reflects the current status of schooling of the child, receiving a one if the child currently studies or is in summer holiday, and zero otherwise. The second variable – schooling gap refers to the difference between the expected grade according to a child's age and the actual completed grade of his/hers, defined as follow.

$$\text{Schooling Gap} = \max\{0, \text{expected grade} - \text{actual grade}\}$$

Where,

$$\text{Expected} = \left\{ \begin{array}{l} 0 \text{ if age} \leq 6 \\ (\text{age} - 6) \text{ if age} \geq 7 \end{array} \right\}$$

This measure was initiated by Maldonado and Gonzalez-Vega (2008) in their study for Bolivia, and followed by many other studies on child schooling (You and Annim, 2014 and Islam and Choe, 2013). It receives a zero if the child successfully completes his/her current degree of education without any late entry, repeated grades or drop-out. A greater-than-zero value is assigned when the child encounters any problems mentioned above. The greater positive values of this variable the lower quality of education attained to the child. As such, this measure is aimed to reflect the quality of education, rather than just whether or not attending school. Apparently, schooling gap is by nature not a cardinal variable as disparity in the quality of education of smaller gaps differ from that of bigger gaps. Accordingly, this variable should not be estimated with least squares methods, but instead in a framework of an ordered response model as it considers "the naturally ordered scale" and "a discrete ordered observed outcome" that exactly reveals the quantitative meaning of our schooling gap variable (Greene, 2012, Wooldridge, 2010, Zavoina and McElvey, 1975).

For child work, we use average hours per day children engage in different types of work over the past 12 months. Within a labor activity that children are involved, we distinguish between hired work and self-employed work. Hired work refers to informal jobs children undertake at other households where they work as hired labor in exchange for wages or salaries

[5] We noted a possible candidate for school attendance is a dichotomous dummy variable indicating whether the child attended school in the past year. While this measure has been widely used in empirical studies on schooling, its information appears to be essentially missing in our dataset. Consequently, we resort our measure of school attendance to the current status of schooling.

in cash or in kind. Self-employed work include both farm and non-farm activities at their own households for household production or consumption purposes. We notice the former category represents a small percentage according to our sample of approximately 2 percent across years, indicating that most of children work at their home.

Table 1 presents some key descriptive information of child work and child schooling for each year of our pooled sample. Amongst the sample children of rural households aged 6 – 15, as much as 10 percent of them are active in either type of work in 2010 and this figure declines in the subsequent years of 2012 and 2014. The proportion of children's participation in hired works is very low, and decreases over three years – from 2 percent in 2010, to 1.5 percent in 2012, and to 1.3 percent in 2014. The proportion of children's participation in self-employed work is much higher than in hired work, and has nonetheless fallen from 13 percent in 2010 to 7.5 percent in 2014. The majority of children engaged in self-employed work involve farming activities. With regards to work intensity, the work load of children is noticeably high for hired work throughout the years. On average, each working child devotes approximately seven hours per day as hired labor, while spending much less, namely a half of day for self-employed work. Across three years, the average hours worked by children in either type of work amounts to 4.7 hours per day or approximately 33 hours per week, which is substantially higher than a cut off level of 14 hours per week on which a child is defined by SYMPOC as economically active laborer (ILO, 2013). While this figure follows a slightly decreasing trend, it indicates a severe situation of child labor in rural Vietnam. Indicators for schooling outcomes of children are also highlighted in table 1. The overall school attendance rate is as high as 97 percent and remains stable across years. The schooling gap has been slightly narrower over time, indicating some improvement in child schooling in rural Vietnam.

An interesting pattern emerges from analysing child schooling outcomes conditional on the working status of children. The school attendance rate is almost comparable between the two groups of working children vs their non-working peers. As with schooling gap, interestingly, working children appear to have a schooling gap significantly larger than their non-working peers. On average, non-working children have a gap of 1.53 years, while those children who work as hired labour suffer from a bigger gap of 3.3 years. This provides an indication of a trade-off currently faced by working children between work and schooling, which will be empirically examined in the next section.

Table 1

Work and schooling status for children 6-15 in rural Vietnam 2010 – 2012 – 2014

	2010			2012			2014		
Variable	Obs.	Mean	S.D	Obs.	Mean	S.D	Obs.	Mean	S.D
Participation rate (%)									
Either work	4,796	0.139	0.346	4464	0.112	0.316	4265	0.083	0.275
Hired work	4,796	0.020	0.141	4464	0.015	0.122	4265	0.013	0.114
Self-employed work	4,796	0.127	0.333	4464	0.102	0.303	4265	0.075	0.264
of which: Farm	4,796	0.122	0.327	4464	0.098	0.298	4265	0.072	0.259
Non-farm	4,796	0.006	0.080	4464	0.006	0.075	4265	0.004	0.061
Work intensity of working children (hour/day)									
Average either work	669	4.785	2.146	502	4.598	2.269	352	4.648	2.290
Average hired work	97	6.825	2.041	67	7.119	2.041	56	6.625	2.316
Average self- employed work	611	4.566	2.024	457	4.330	2.113	321	4.424	2.178
of which: Farm	583	4.528	1.943	439	4.355	2.087	308	4.393	2.134
Non-farm	31	5.258	3.204	25	3.440	2.417	16	4.688	2.960
School attendance (%)	4,796	0.972	0.164	4,464	0.973	0.162	4,265	0.976	0.154
Conditional on participation in									
Either work	669	0.960	0.197	502	0.966	0.181	352	0.952	0.215
Hired work	97	0.948	0.222	67	0.970	0.171	56	0.911	0.288
Self- employed work	611	0.957	0.202	457	0.965	0.184	321	0.950	0.218
of which: Farm	583	0.955	0.207	439	0.964	0.188	308	0.948	0.222
Non-farm	31	1.000	0.000	25	1.000	0.000	16	1.000	0.000
Aver. schooling gap (years)	4,265	1.530	1.070	4,464	1.560	1.110	4,796	1.430	1.200
Conditional on participation in									
Either work	669	2.345	0.080	502	2.488	0.089	352	2.500	0.110
Hired work	97	3.309	0.264	67	3.492	0.257	56	3.857	0.336
Self- employed work	611	2.257	0.082	457	2.376	0.091	321	2.377	0.112
of which: Farm	583	2.292	0.085	439	2.412	0.094	308	2.389	0.116
Non-farm	31	1.484	0.201	25	1.680	0.189	16	2.063	0.193

Source: tabulated by authors from VHLSSs 2010, 2012, 2014

Table 2 further compares the work and schooling status of children according to whether the respective household participated in the microcredit program provided by VBSP, using the panel sample of 1,761 children aged 6-15. Also in this table, key independent variables of the two sub-samples are presented. Across years, children from households that participated in the VBSP tend to have a significantly higher chance to work and on average work for longer hours than children from non-participating households. Nevertheless, irrespective of credit participation status, both propensity to work and work intensity slightly decline overtime. As to schooling status, a remarkable difference between the two groups emerged in 2010 but not in 2012 and 2014: credit participant's children have a lower attendance rate and accumulate a clearly larger schooling gap. Schooling outcomes, both in terms of school attendance and schooling gap, seem to converge over time, with respect to credit participation.

With regards to the right-hand side variables, a few interesting patterns are observed. While children from the two sub-samples are very similar in age, gender distribution is skewed toward males for households that are credit recipients. Household attributes also differ according to credit participation status. Relative to the households without credit participation, credit participating households are evidently poorer, and larger in size. Credit participating households are also more likely from an ethnic group minority and possess less meter squares of land than their non-credit participating counterparts. Mothers of children from credit participating households seem to be engaged more in current employment compared to non-participating households. Overall, the description suggests that the non-credit participation, known as the control group and the credit participation, referred to as the treatment group differ in several ways, and that it is critical to account for this difference when estimating the impact of credit on the outcome variables.

Table 2

Sample characteristics of child schooling and work, according to household participation in the VBSP microcredit program.

	2010		2012		2014	
	Non-Credit Participation	Credit Participation	Non-Credit Participation	Credit Participation	Non-Credit Participation	Credit Participation
Work participation rate (%)						
Hired work	2.060	0.960	1.210	2.000	0.850	0.970
Self- employed work	11.340	25.960	8.670	17.000	4.020	7.770
Either work	12.580	25.960	9.480	18.000	4.440	8.740
Work intensity of working children (average hours/day)						
Hired-work	7.200	3.000	6.833	5.500	5.500	5.000
Self-employed work	4.218	4.375	4.093	4.176	4.105	4.375
Either work	4.229	4.370	3.681	3.889	4.190	4.444
Schooling by children						
School attendance (%)	96.701	95.192	97.782	96.000	97.252	96.058
Avg. schooling gap (yr.)	1.332	1.529	1.665	1.770	2.057	2.068
Children attributes						
Aver. age of children	10.056	10.115	10.502	10.590	10.368	10.398
Male children (%)	46.392	47.115	51.008	57.000	50.106	57.281
Household attributes						
Poor households (%)	12.784	56.731	15.524	62.000	16.068	32.039
Household size (person)	4.656	5.029	4.702	4.770	4.529	4.553
Average land asset per head (m^2)	15.755	11.568	15.827	12.929	17.368	14.370
Ethnic head household (%)	25.773	79.810	30.242	64.000	28.753	61.165
Average age of mother (yrs)	35.324	35.058	35.478	35.070	35.814	35.495
Mothers as head (%)	9.691	1.923	9.274	9.000	10.782	7.767
Mothers having job (%)	96.907	99.038	94.758	95.000	95.560	96.117
Average credit intake per household (thousands VND)		11,313		15,081		18,471
Average credit intake per head (thousands VND)		2,300		3,143		4,068

Source: tabulated by authors from VHLSSs 2010, 2012, 2014

IV. EMPIRICAL STRATEGY

A. Model specification

Our objective is to discern a causal impact of microcredit participation on the schooling and work outcomes of children from rural households. Because the two outcomes of child schooling and child labor are determined within a household, child schooling and child labor are modelled to be conditional on individual (child) endowments, parent endowments, household characteristics, and household credit in our empirical framework. Our key model of child work versus child schooling is specified as follows.

$$\boldsymbol{Y}_{ijt} = \boldsymbol{\alpha} + \boldsymbol{I}_{ijt}\boldsymbol{\beta}_1 + \boldsymbol{X}_{ijt}\boldsymbol{\beta}_2 + \boldsymbol{Year}_t\boldsymbol{\beta}_3 + \boldsymbol{C}_{ijt}\boldsymbol{\lambda} + \boldsymbol{\varepsilon}_{ijt} \quad (1)$$

Where Y is the schooling/labor outcome[6] of child *i* in household *j* in year *t*. α is constant term. ***I*** refers to a set of individual endowments including age and gender of the child, as commonly done in the literature on schooling. *X* is a vector of parent attributes and household characteristics that control for observed attributes that determine schooling/labor outcomes of the child.

In this model, household credit *C* is measured by two participation indicators. The first assumes whether a household participated in the program in the survey year (a dichotomous treatment variable), while the second captures the actual accumulated loan intake by each of member in the household in years preceding to the survey time (a continuous treatment measure). Age of mothers and parents is included as it may influence their decision to send their children to school or to work. Gender empowerment, a relevant factor for children's well-being (Pitt and Khandker, 1998), is captured by two indicators, namely whether the mother is the household head and whether the mother is currently in employment. Household characteristics should also underlie the schooling and labor outcomes of the children. We therefore introduce several variables that indicate household economic background, namely whether the household is poor according to the commune authority criteria, whether the household is from a minor ethnic group and household asset holdings measured by total areas of owned land (see Edmonds (2007)

[6] We note that the child labor outcomes measured by average hours worked per day are in discrete form, including a value of zero. So, a log transformation should be attempted before we can treat them as continuous variables and use least squares regressions. We follow a widely suggested remedy for taking logs of zero, that is to add a constant of small value (say, 0.1) to the original figures before logging.

for detailed motivation of the inclusion of these covariates). Finally, *Year* is a year dummy that controls for a year-fixed effect on the outcome variables. Table A1, and A2 in the appendix provides a full description of all variables.

As predicted by theory, credit can induce either a positive effect or a negative effect on the amount of work undertaken by children. If a positive effect is observed, credit is sought to bring about a higher demand for child labor, which may arise from a relative increase in productivity of child labor, or from a difficulty in using hired labor as a child labor substitute (the so-called home-enterprise capitalization effect). Alternatively, a negative effect emerges when the use of hired labor is facilitated with a household's increased access to credit (the so-called family labor substitution effect), or when credit stimulates parent's investment in schooling of their children (the welfare effect and/or the risk management effect). Since the intensity of child work is the reverse of child schooling, an opposite effect on schooling is expected.

The key variable of our interest is C, microcredit participation, captured by both the participation indicator dummy and the actual amount of credit received by each of member in household. While the use of reported amount of credit may be subject to misreporting or other types of measurement errors, as well acknowledged by Islam and Choe (2013), credit participation dummy is less prone to measurement errors. To examine the causal impact of microfinance on household decision on both child schooling and child work, it is critical to address the possible endogeneity of credit caused by unobserved determinants of household's decision to participate in a microfinance programme and of the decision on how much to borrow, which may also influence the household decision on child schooling and child work. This requires an estimation technique that disentangles the impact of microfinance from the impact of all observed and unobserved attributes that affect the child welfare. We note that due to the problem of potential endogeneity of credit, most of the existing studies on this field have refrained from the use of credit participation as a credit variable. Instead, they have introduced indirect measures of credit, for example, self-assessed credit limit by Hazarika and Sarangi (2008), or membership dummy by Maldonado and Gonzalez-Vega (2008). While using these measures to some extent can relieve the endogeneity problem of credit, it is unable to reveal the effectiveness of the credit programs that are in operation, and thus the derived findings appear to be less policy relevant as compared to using direct measures of credit participation.

B. Estimation techniques

We pursue different econometric techniques to exploit the panel feature of our data and to control the endogeneity for microcredit. To estimate the impact of credit on child labor outcome, we use the instrumental variable within random effects Baltagi-Chang generalized least square[7] and the two- step generalized structural equation model with first stage probit, for the actual amount of credit intake by each member in the household and the dichotomous credit participation dummy, respectively. To discern the impact of credit on child schooling gap, we employ a fully observed recursive mixed-process model that includes two cases of endogeneity: (i) the recursive ordered probit model with first stage probit; and (ii) the recursive ordered probit model with first stage uncensored. Detail of each of these methods is presented in the appendix A3.

In all three estimation methods implemented in this study, an IV application requires an appropriate choice of instruments which are variables that are highly correlated with decision to participate in the credit program, and with the size of microcredit, but are not correlated with the outcome variable. We use the indicator for the microcredit program placement in the residence commune of the household, interacted with household attributes (defined as X in equation (1)) as instruments for credit participation. While the program placement reflects the availability of credit that a household may have access to, it is exogenous to households and to household decisions on child schooling/work. Because of this, this variable has been used in previous studies as an indicator for households' access to credit (Lensink and Pham, 2012, Ersaco, 2005). We further argue that an interaction between this program placement and household's characteristics will reflect households' ability to participate in the credit program and/or to how much to borrow, while having no direct impact on the household's decision on work and schooling of children.

[7] Choice of random effects estimator is justified based on Hausman test. The test results show that the null hypothesis is not rejected. It means that the coefficients of the two models (fixed versus random effects) are equal, fixed effects estimates are still unbiased, but its standard errors will be higher than the standard errors in the random effects model. In this case, the random effects model will be more efficient than fixed effects model

V. RESULTS

A. The impact of microcredit on child work

Tables 3 and 4 present our estimation results of child labor conditional on microcredit participation and other covariates at both individual and household levels. In both tables, child work is measured in as the logarithm of average hours spent per day for either hired work or self-employed activities at home (self-employed work). Table 3 reports the effects of microcredit on work intensity of children, with IV random effects Baltagi-Change GLS estimators of the credit amount received per household member, while table 4 shows the effect of credit participation dummy on the same outcome variables fitted in a structural equation model. Irrespective of how microcredit participation is measured, either as a dichotomous participation dummy or a continuous credit amount, all coefficients associated with work intensity of children for self-employed work and total work are statistically significant. From the table 3, given an additional unit of credit received calculated on the basis of average credit per member within the household, children of this microcredit recipient tend to engage 1.0002 more hours in self-employed work and 1.00018 more hours in total work, *ceteris paribus,* compared to their peers. Consistent with Hazarika and Sarangi (2008)'s finding of an increase of the probability of children to work in rural Malawi due to increased access to credit by households, our result emphasizes the positive impact of credit on the work load carried by children, in other words, children work longer per day when more credit is provided to the household, and mostly in self-employed work, not work as hired labor.

Except for the estimates of average hours of hired-work[8], all instrument tests suggest that microcredit is endogenous, and the selected instruments are strong and valid within the IV random effects Baltagi-Chang GLS framework. This offers a strong credence to our estimates of the effects of credit on child labor outcomes. Results of the instrument test are provided in the last four rows of the table 3. Firstly, results of Sargan-Hansen tests of over-identifying restriction appear to be insignificant that the instruments used do not exceed the number of regressors, which implies valid instruments. Second, the conditional likelihood ratios test (Moreira, 2003) reports a significant p-value which confirms appropriate instruments, and the main regressor

[8] Various econometric techniques have been attempted but failed to identify the effect of microcredit on hired work. Perhaps a small proportion of the sample –1.36% recorded as hired labor makes it insufficient to reveal the effect of microcredit on this type of child labor.

(microcredit participation) should be treated as an endogenous variable in this empirical model. In the last two rows, results of the Anderson-Rubin test and bounded LM score test confirm strong and accurate instruments, rejecting the null hypothesis that instruments are weak.

The results presented in table 4 further confirm the impact of microcredit participation on the work intensity of children with a dichotomous participation dummy as the treatment variable. Compared to non-credit participating households, children of microcredit recipients engage 1.269 hours more in self-employed work and 1.257 hours more in either work. The significant values of the diagnostic test (Wald test) and the IV coefficients of the first stage regression prove that the appropriate instruments have been in place. The statistical diagnostic test - Bonferroni-adjusted Wald test - of the composite fitted full model confirm that all models in both stages of GSEM model are accurate. It means that the applied two-stage regression with IV probit model is relevant and justifiable.

The signs of several control variables merit some attention as they appear to be consistent in both estimates of the impact of the credit amount and credit participation dummy. The coefficients on year dummies indicate that an average child works less hours in 2012 and 2014 compared to the base year of 2010, consistent with our descriptive analysis in section 3. This may be indication of a narrower gap in the work load carried by working children relative to their non-working peers. Older children work more, both as hired labourer and self-employed worker at their home. Boys spend more time in both types of work as compared to girls, as also found by Edmonds and Turk (2004) for Vietnam and as well observed in other developing countries (Hazarika and Sarangi, 2008 for the case of Malawi, and Maldonado and Gonzalez-Vega, 2008 for the case of Bolivia). Children from an ethnic minority-headed household tend to work much more, suggesting evidence of an ethnic disparity as also documented in other studies for rural Vietnam (Rew, 2009). Further, in line with other studies that find a strong association between land or household assets holdings and child work intensity (Maldonado and Gonzalez-Vega, 2008, Hazarika and Sarangi, 2008, Najeeb Shafiq, 2007), our results indicate that children from more well-off households, households possessing more land, tend to be less involved in work, either as hired labourer or work-at-home. Variables those capture gender aspects suggest a number of interesting results as well. First, the older the father is, the fewer hours the children have to work. A possible explanation is that younger fathers are more likely to work away from home, leaving the burden of home work for their children. On the contrary, children of older mothers tend to work more, perhaps to generate more income for the household.

Table 3

The impact of credit amount per member in household on child work

Variables	Average hours hired work	Average hours self-employed work	Average hours either work
Credit amount per member	-0.000008	0.000201***	0.000184***
(thousands VND)	(0.00002)	(0.00005)	(0.00005)
Gender (1/0)	0.090615***	0.038761*	0.088447*
	(0.02249)	(0.04978)	(0.05145)
Child age (yrs)	0.024039***	0.104147***	0.119509***
	(0.00422)	(0.00934)	(0.00965)
Ethnic-head household (1/0)	-0.000062	0.033914***	0.029541***
	(0.00216)	(0.00478)	(0.00494)
Land asset per member (meter squared)	-0.003122**	-0.003201*	-0.004877*
	(0.00129)	(0.00285)	(0.00294)
Mother age (yrs)	0.005130**	0.014624***	0.016916***
	(0.00223)	(0.00493)	(0.00509)
Mother as household head (1/0)	-0.004526	-0.119111	-0.135787
	(0.04621)	(0.10229)	(0.10573)
Mother having job (1/0)	0.026585	0.017989	0.061048
	(0.06263)	(0.13863)	(0.14328)
Father age (yrs)	-0.003312**	-0.006967**	-0.011190***
	(0.00154)	(0.00341)	(0.00353)
Year 2012	-0.021206	-0.170179***	-0.176360***
	(0.02737)	(0.06058)	(0.06261)
Year 2014	-0.038409	-0.400218***	-0.415621***
	(0.02833)	(0.06270)	(0.06481)
Constant	-2.560155***	-3.334800***	-3.397469***
	(0.08568)	(0.18966)	(0.19603)
First stage regression			
Placement * poor household	764.271***	764.271***	764.271***
	(106.756)	(106.756)	(106.756)
Placement * ethnic-head	41.166***	41.166***	41.166***
	(10.905)	(10.905)	(10.905)
Placement * land asset per mem.	33.925***	33.925***	33.925***
	(4.038)	(4.038)	(4.038)
Constant	317.27	317.27	317.27
	(254.357)	(254.357)	(254.357)
No. Obs.	1761	1761	1761
Sargan-Hansen test of overidentifying	0.737	0.820	0.776
Conditional LR test	0.7125	0.0000	0.0001
Anderson-Rubin test	0.0964	0.0002	0.0017
LM score test	0.7147	0.0000	0.0010

Notes: Dependent variables are the logarithm of child work hours in each type of work. The IV estimates within random effects Baltagi-Chang GLS are reportedd. IVs are the interactions between the placement of credit program (commune level) and the household characteristics. Standard errors are in parentheses; ***, **, * denote the significance at 1-, 5-, 10- percent level, respectively.

Table 4

The impact of credit participation on child work

Variables	Average hours hired work	Average hours self-employed work	Average hours either work
Credit participation (1/0)	-0.021214	0.238371***	0.228851***
	(0.03017)	(0.06443)	(0.06707)
Gender (1/0)	0.086992***	0.046209*	0.093039*
	(0.02235)	(0.04773)	(0.04969)
Child age (yrs)	0.024063***	0.099837***	0.115567***
	(0.00417)	(0.00891)	(0.00927)
Ethnic-head household (1/0)	0.000494	0.036203***	0.031806***
	(0.00210)	(0.00448)	(0.00466)
Land asset per member (meter squared)	-0.000736**	-0.000580	-0.000983
	(0.00030)	(0.00065)	(0.00067)
Mother age (yrs)	0.005012**	0.016902***	0.018918***
	(0.00219)	(0.00468)	(0.00487)
Mother as household head (1/0)	-0.009341	-0.149709	-0.165529
	(0.04589)	(0.09801)	(0.10203)
Mother having job (1/0)	0.025313	0.008914	0.052390
	(0.06241)	(0.13328)	(0.13876)
Father age (yrs)	-0.002959*	-0.007354**	-0.011286***
	(0.00153)	(0.00327)	(0.00341)
Year 2012	-0.021928	-0.147798**	-0.155611**
	(0.02720)	(0.05808)	(0.06047)
Year 2014	-0.040830	-0.346786***	-0.367027***
	(0.02753)	(0.05880)	(0.06122)
Constant	-2.564309***	-3.332064***	-3.401257***
	(0.08497)	(0.18147)	(0.18892)
First stage regression			
Placement * poor household	1.271053***	1.271053***	1.271053***
	(0.10259)	(0.10259)	(0.10259)
Placement * ethnic-head	0.060357***	0.060357***	0.060357***
	(0.00824)	(0.00824)	(0.00824)
Placement * land asset per mem.	0.008798***	0.008798***	0.008798***
	(0.00098)	(0.00098)	(0.00098)
Constant	-1.772216***	-1.772216***	-1.772216***
	(0.06897)	(0.06897)	(0.06897)
No. obs.	1761	1761	1761
First stage			
Wald chi2(3)	411.050	411.050	411.050
Pro>chi2	0.000	0.000	0.000
Fitted full model			
Bonferroni-adjusted Wald test (chi-square)	487.640	731.610	753.890
Bonferroni-adjusted Wald test (P-value)	0.000	0.000	0.000

Notes: Dependent variables are logarithm of child work hours in each type work. The IV estimates within a generalized structural equation model with first stage probit are reported. IVs are the interactions between the placement of credit program (commune level) and the household characteristics. Standard errors are in parentheses; ***, **, * denote the significance at 1-, 5-, 10- percent level, respectively.

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B. The impact of microcredit on child schooling

The table 5 reports the effects of microcredit on child schooling gap, estimated by fully observed recursive mixed-process models, in which we distinguish the recursive ordered probit model from first stage uncensored where the endogenous variable is the amount of credit intake per member in the household – a continuous variable; and the recursive ordered probit model with first stage probit where the endogenous variable is a dichotomous credit participation dummy. As noted in section 3, the *schooling gap* variable measures the quality of education that varies according to the gap size as the quality of education reflected by smaller gaps differ from that of bigger gaps. Accordingly, recursive ordered probit models are employed to estimate the average effect of microcredit on schooling gap, and also reveal the marginal effect of credit at each category of the gap.

The results of both recursive ordered probit models presented in columns (2) and (3) of table 5 show that credit participation by households, on average, widen the schooling gap among children of the recipients, as evident from statistically significant positive coefficients associated with both continuous and dichotomous measures of credit participation. The significant values of all reported coefficients in the first stage regression confirm the relevant and justifiable econometric estimations. Most of instrumental variables have a significant value at 1 percent level, validating a strong application of IV. While microcredit, on average, appears to have a negative impact on child schooling, widening the gap and thereby lowering the quality of education, interestingly this effect varies according to the category of schooling gap, as shown in columns (3) and (4) of table 5. Columns (3) and (4) include the marginal effect of credit amount and credit participation on each category of schooling gap, respectively. While a negative marginal effect of credit is identified for the first gap of schooling, a positive marginal effect emerges for most of the subsequent gaps, which confirms the consistency of our coefficient estimates reported in columns (2) and (3). Holding everything else constant, one additional unit of microcredit intake (1 million VND) would induce a reduction of 5.6 percentage points in the probability of having 1-year lagged behind the expected grade by the respective children. On the other hand, the same increment of credit would cause a rise of 3.1 percentage points in the probability of having 2-year lagged behind the expected grade, a rise of 2 percentage points in the probability of having 3-year lagged behind the expected grade and so on.

Table 5

The impact of microcredit participation on child schooling

Variables	The estimated model		The marginal effect dy/dx of microcredit on schooling gap		
	Model 1	Model 2	Gaps	Credit amount per member	Credit participation dummy
Credit amount per member	0.000189***				
(thousands VND)	(0.000052)				
Credit participation dummy (1/0)		0.423743***	1	-0.000056***	-0.131304***
		(0.15228)		(0.0000140)	(0.045245)
Gender (1/0)	0.146225***	0.151622***	2	0.000031 ***	0.071283***
	(0.05049)	(0.05151)		(0.0000079)	(0.024443)
Child age (yrs)	0.099466***	0.102271***	3	0 .000020***	0.047649***
	(0.00969)	(0.00966)		(0.0000052)	(0.016968)
Ethnic-head household (1/0)	0.017846***	0.017011***	4	0.000008***	0.018384**
	(0.00541)	(0.00574)		(0.0000024)	(0.007255)
Land asset per member (m^2)	-0.003715	-0.003394	5	0.000005***	0.009619**
	(0.00282)	(0.00296)		(0.0000016)	(0.004023)
Mother age (yrs)	0.003059	0.003336	6	0.000002*	0.003364*
	(0.00513)	(0.00527)		(0.0000008)	(0.001913)
Mother as household head (1/0)	-0.040320	-0.043678	7	0.000001*	0.002372
	(0.09345)	(0.09596)		(0.0000007)	(0.001485)
Mother having job (1/0)	-0.280824**	-0.292513**	8	0.000001	0.001881
	(0.12317)	(0.12783)		(0.0000007)	(0.001338)
Father age (yrs)	-0.006198*	-0.006456*	9	0.000001	0.001319
	(0.00334)	(0.00341)		(0.0000006)	(0.001048)
Year 2012	0.534261***	0.534972***	10	0.000001	0.002090
	(0.07729)	(0.07760)		(0.0000011)	(0.001445)
Year 2014	1.215217***	1.223079***			
	(0.07769)	(0.07580)			
First stage regression					
Placement * poor household	810.380011***	1.279832***			
	(168.05528)	(0.10619)			
Placement * ethnic-head	31.424945*	0.061491***			
	(16.86168)	(0.00963)			
Placement * land asset	32.748563***	0.039657***			
	(4.77029)	(0.00422)			
Constant	98.906830***	-1.782537***			
	(21.66073)	(0.05224)			
No of obs.	1761	1761			
First stage					
F statistic	92.730	492.570			
Pro> F	0.000	0.000			
R-square	0.137	0.302			
Fitted full model					
Wald chi-square	701.540	995.060			
Pro>chi-square	0.000	0.000			

Notes: Dependent variable is the ordered category variable – schooling gap. IV estimates within fully observed recursive mixed-process models are reported, with the recursive ordered probit model with first stage uncensored in Model 1; and for the recursive ordered probit model with first stage probit in Model 2. Standard errors are in parentheses; ***, **, * denote the significance at 1-, 5-, 10- percent level, respectively.

The marginal effects of the credit participation dummy on various categories of schooling gap, as included in column 4 of table 5, also follow a similar pattern, showing that the effect is only desirable for the first gap of schooling and become undesirable for the subsequent gaps.

While our finding of an average adverse impact of microcredit on child schooling is consistent with Islam and Choe (2013) for rural Bangladesh, in which schooling gap is also used to measure the quality of child education, our marginal effects at each category of the schooling gap offer further insights into the influence of credit on child's education among microcredit recipients. A possible interpretation for this interesting finding could be drawn on two competing theoretical arguments for the impact of credit on child labor and child schooling, the so-called welfare effect (Rajan, 2001) vs. the 'home enterprise capitalization' effect (Wydick, 1999). As children of the microcredit recipients encounter early problems in their schooling, as they are in their first schooling gap, the welfare effect of credit takes place and therefore increased access to microcredit would lower the probability of pulling these children out of school. However, once children have been long put to work and accordingly suffering from more than one year lagged behind their expected grade, reflected by a bigger schooling gap, additional borrowing of the households would exacerbate the problem as the 'home enterprise capitalization' effect dominates the welfare effect, precipitating the children to work more.

The signs of control variables reveal some interesting and consistent findings across both models of credit amount and credit participation. Boys appear to have lower quality of schooling, reflected by a wider schooling gap. Older children seem to suffer more from lagging behind their expected grade. Children from ethnic-headed families are more likely to encounter a bigger schooling gap. Interestingly but not surprisingly, the child would have better schooling if his/her mother has a job, perhaps the child would have to work less, as earlier discussed in section 5.1. While the effect of mother age on child education is not statistically significant, older fathers seem to offer a clear benefit to child schooling, evident from a smaller schooling gap. Note that, children of older fathers, *ceteris paribus*, also appear to work less, as reported earlier. Finally, coefficients of both year dummies for 2012 and 2014 are positive and statistically significant, revealing an upward trend of schooling gap, conditional on other covariates.

In sum, we find strong evidence of a positive effect of credit on child work, lending support to the 'home enterprise capitalization' hypothesis by Wydick (1999). It indicates that improved access to credit enables households to expand their production activities by acquiring more capital inputs, and thus precipitating them to practice more child labor, especially in self-employed activities. Due to this credit-stimulated economic activity, children tend to be less involved in schooling, as evident from an adverse impact of credit on schooling gap among children of the microcredit recipients. Following Islam and Choe (2013) , Ravallion and Wodon (2000) and Hazarika and Sarangi (2008), we argue that the increased child work may arrive at a trade-off with less time and resources devoted for learning, thereby lowering the quality of education.

VI. CONCLUSIONS

Given the substantial outreach of microcredit programs in developing countries, and an increased focus on a wide range of poverty reduction targets by these programs, an assessment of the causal link between microfinance and two important outcomes of poverty, namely child education and child labor, provides a better understanding of the multi-dimension impact of microfinance for the developing world.

Using the data from the most recent household surveys for Vietnam 2010 - 2014, we investigate the impact of actual participation in a microcredit program on household decision on child schooling and child labor for rural Vietnam. Compared to existing studies on the field, our present study offers several unique features. First, a large sample with the panel structure enables us to exploit the dynamics in child work and schooling status over time, conditional on microcredit and other relevant covariates. Second, unlike indirect measures of credit, actual participation in the microcredit program (both participation dummy and credit amount) allows us to discern the effectiveness of the microcredit program in operation. In this way, the revealed findings are highly policy relevant. Third, to capture the causal impact of credit, the IV method is featured in various models including a random effects model, a generalized structural equation with first stage probit model, and a fully observed recursive mixed-process model. Our current choice of instrument, that is the program placement, and its interaction with other household variables, appears to be appropriate in all estimation equations, thereby providing unbiased estimates of the impact of credit on child labor and schooling outcomes. Last, but not least, *schooling gap*, our measure of schooling outcome is treated as an ordered variable in the framework of ordered response models, which go beyond the framework of ordinary least squares as commonly done in previous studies on schooling.

We find that credit participation by households motivates children to spend more time in self-employed activities, but not in hired work. This increase in child work can be attributed to a child-labor demand effect of the business/production expansion, which is encouraged by an increased access to credit of the household. On the causal linkage between schooling gap and credit, we find that credit participation by households tends to lower the quality of education of their children, and this undesirable effect is strongly observed for schooling gaps of more than one year. In other words, if a child is far lagged behind his/her expected schooling, reflected by large categories of schooling gap, then microcredit appears to exacerbate this problem.

Overall, the study raises several important concerns for policy makers. First, it provides a serious warning for the case of Vietnam that credit-stimulated work at households that participated in the microcredit program may in fact stimulate more child work, and that credit-induced child labor activities may be deleterious to the well-being of children, and accordingly lower the quality of education the child would have attained otherwise. Second, because of the above, while microcredit programs may enhance household welfare and help the poor out of poverty as is widely acknowledged, the contribution of microfinance may not be truly in accordance with poverty reduction targets Millennium Development Goals (MDGs), in which child labor reduction is a critical concern. Finally, it is suggested that concern for child labor should be taken into consideration when introducing and evaluating a microcredit program that targets the poor in the developing world.

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Appendix

A1. Variable summary

	2010		2012		2014	
Variables	Mean	S.D	Mean	S.D	Mean	S.D
Dependent variables- Child labor/ schooling outcomes						
Average hours either work (log hours/day)	-2.219	0.588	-1.889	1.179	-1.998	1.030
Average hours hired-work (log hours/day)	-1.829	1.251	-2.239	0.514	-2.249	0.470
Average hours self-work (log hours/day)	-1.778	1.315	-1.931	1.115	-2.028	0.975
Schooling gap	1.436	1.202	1.558	1.110	1.529	1.067
Credit variables						
Participation dummy (1/0)	0.175	0.380	.1659946	.3721175	0.198	0.399
The accumulated amount of credit received per head in each household (thousand VND)	402.853	1111.627	521.656	1502.459	807.000	2179.429
Child attributes						
Child age (years)	10.701	2.930	10.567	2.884	10.516	2.852
Child gender (1/0, 1 for male)	0.519	0.500	0.517	0.500	0.518	0.500
Household attributes						
Poor household dummy (1/0)	0.192	0.394	0.223	0.416	0.181	0.385
Ethnic-headed household dummy (1/0)	3.573	5.946	3.686	6.084	3.690	6.262
land asset per household (m2)	66.036	37.305	70.959	39.273	75.269	42.808
land asset per head (m2)	14.229	8.912	15.369	9.092	16.703	10.234
Parents attributes						
Mother age (years)	32.314	14.375	30.907	15.008	29.795	15.783
Father age (years)	33.129	16.163	31.980	16.777	30.51606	17.64847
Mother as household head dummy (1/0)	0.094	0.292	0.090	0.286	0.091	0.287
Mother having job dummy (1/0)	0.840	0.370	0.807	0.395	0.781	0.414
Number of observation	4796		4764		4265	

A2. Variable definitions

Variables	Definitions
Dependent variables	
Child labor and schooling outcomes	
Average hours either work (log hours/day)	The average hours per day (in logarithm) of child labor in either type of work in the past 12 months.
Average hours hired-work (log hours/day)	The average hours (in logarithm) of child work a hired laborer – the child works for wages/salaries employment in other households (according to VHLSS classification).
Average hours self-work (log hours/day)	The average hours (in logarithm) of child work as a self-employed worker – the child is involved in farm and non-farm activities at their own households for household production or consumption purposes (according to VHLSS classification).
Schooling gap	The differences between expected graded according to child's age vs. the actual completed grade.
Credit variables	
Participation dummy (1/0)	Whether a household participates in the microcredit program (Vietnam Bank for Social Policy - VBPS)
The accumulated amount of credit received per member in household (thousand VND)	The actual amount loan intake by the household in years of preceding to the survey time/household size
Microcredit program placement dummy (1/0)	Whether a microcredit program of VBSP is present in the commune where the household resides.
Child attributes	
Child age (years)	Age of the child
Child gender (1/0, 1 for male)	The child gender, recorded 1 for male, 0 for female
Household attributes	
Poor household dummy (1/0)	Whether the household is poor according to the commune authority criteria, self-reported by the household.
Ethnic-headed household dummy (1/0)	Whether the household is from a minor ethnic group.
Land asset per household (m2)	Land asset holding by household.
Land asset per head (m2)	Land asset holding by each member in the household.
Parents attributes	
Mother age (years)	Age of the surveyed child's mother.
Father age (years)	Age of the surveyed child's father.
Mother as household head dummy (1/0)	Whether the mother is the household head
Mother having job dummy (1/0)	Whether mother is currently in employment.

A3. Detail of econometric methods.

In the first econometric technique, an IV method within random effects Baltagi-Chang Generalize least square will be used to estimate the impact of the amount of credit received per member in household on child labor outcome. As discussed in Stata press 14 (2015), Baltagi and Chang (2000), Amemiya (1971), Swamy and Arora (1972), Baltagi and Li (1992), White (2001), the two stage least square error component models and the Feasible GLS will be implemented when the inconsistent fixed effects model is concerned, the variation across entities is conditioned to be random and uncorrelated with predictor, and the endogenous problem has been occurred. Let's consider the following equations of IV and two-stage least squares for panel-data model (xtivreg):

$$y_{it} = X_{it}\delta + \mu_i + \upsilon_{it} = Y_{it}\gamma + Z_{1it}\beta + \mu_i + \upsilon_{it} \quad (*)$$

y_{it} denotes for the schooling labor/ outcome which regress on X_{it} (the actual amount of credit intake) of a vector of observations that correlated with the υ_{it}; the two stage least square regression of y_{it} on X_{it} (endogenous variable) with instruments Z_{it} .

In the second econometric technique, a generalized structural equation with first stage probit model (GSEM) will be attempted to estimate the impact of a dichotomous credit participation dummy on child labor outcome. Maddala and Lahiri (1992), Rabe-Hesketh et. al., (2004), Li and Prabhala (2008), Guo and Frasher (2014), and Stata Press 14 (2015) discuss an issue of instrumented identification when there is a simultaneous presence of dummy endogenous and continuous dependent variables in the panel data model. This problem would be modified within the switching progress of a structural equation model. It means that the maximum likelihood estimation within the mechanism of two-stage probit model will be implemented to specify the biased issue from the endogenous variable. In this strategy, the endogenous variables - the dichotomous participation dummy (Whether or not borrowing from VBSP) – will be estimated by instruments in the first stage probit, and then its adjusted values will be regressed in the second stage uncensored on the continuous outcome variables – child work measured as average hours per day in hired work, self-employed work, and either type of these works.

The third econometric technique is derived to estimate the impact of credit on schooling outcome, measured by the schooling gap variable. As this variable is presented in meaningful orders, fully observed recursive mixed-process models will be attempted. Based on the historical literature of multistage procedures of the fitting mixed models from Geweke (1989), Keane (1994), and Hajivassiliou and McFadden (1998), David Roodman have specified the generation of a number of switching mechanisms from the maximum likelihood models, including: probit, ordered probit, ran-odered probit, multinomial probit, censored and uncensored models, as well as the recursive structural models. This method will perform the odds of convergence to solve the endogeneity, to drop the collinearity, to detect the overlapping samples, and to force the error correlation out of the model. In this study, the conditional mixed process will include two cases: (i) the recursive ordered probit model with first stage probit where the endogenous variable is measured as a dichotomous participation dummy; and (ii) the recursive ordered probit model with first stage uncensored where the endogenous variable is the accumulated amount of credit intake by each member in the household. The former case is similar to the first stage of bivariate SUR model (or treatment effect model) by performing the switching progress of probit model, but different in the second stage when the ordered probit model is used instead of uncensored regression. Let analyze the following equations:

$$\begin{matrix} y_1^* = \theta_1 + \varepsilon_1 \\ y_2^* = \theta_2 + \varepsilon_2 \end{matrix} \text{, where } \begin{matrix} \theta_1 = \beta_1 x \\ \theta_2 = \delta y_1 + \beta_2 x \end{matrix}$$

In the first stage, y_1^* - the credit participation dummy - is regresse on the Z factors of instrumental variables, including microcredit program placement and its interactions with household characteristics. The conditional outcome would be: $\theta_2 = 1$, if $y_1^* > 0$, and $\theta_2 = 0$ otherwise. Then the outcome of the ordered probit in the second stage would be:

$$y_2^* = g(y^*) = \begin{cases} O_1 \; if \;\; c_0 < y^* \le c_1 \\ \vdots \\ O_j \; if \;\; c_{j-1} < y^* \le cj \\ \vdots \\ O_J \; if \;\; c_{J-1} < y^* \le c_J \end{cases}$$

In this study, y_2^* is the ordered category variable – child schooling gap, ranging from 0 to 10; and c presents cut points of these gaps.

The latter case will be estimated differently with the former as the endogenous variables is the amount of credit - an uncensored (or continuous) variable. Since there is a problem of endogeneity $Cov(x,u) \neq 0$, the adjusted linear regression of instrumental variable (Z vectors) will be conducted as following:

$$x = \pi_0 + \pi_1 z + v$$

Where $Cov(z,u) = 0$, and $Cov(z,x) \neq 0$. And, the second stage of schooling gaps estimation will be similar to the former case:

$$y = g(y^*) = \begin{cases} O_1 \ if \ \ c_0 < y^* \leq c_1 \\ \vdots \\ O_j \ if \ c_{j-1} < y^* \leq cj \\ \vdots \\ O_J \ if \ c_{J-1} < y^* \leq c_J \end{cases}$$