# THE IMPACT OF MICROFINANCE LOANS ON CHILDREN'S EDUCATIONAL ATTAINMENT IN RURAL THAILAND

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Undergraduate Honors Thesis

Fall 2011

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# Abstract

The creation of human capital is key in efforts to alleviate poverty in the developing world. As the returns to education are delayed and enrollment in schools is costly, families in underdeveloped nations, especially those who live in rural environments where schools are often not locally situated, can be caught in poverty traps. The less educated and impoverished demand less schooling for their children and, therefore, their children are less able to raise their standard of living. when they reach adulthood. This paper examines the relationship between microfinance loans and the educational attainment of children in rural Thailand. Individual fixed effects are examined and observable differences are controlled for in order to expose the nature of this relationship. The results challenge the claim that microfinance is a working solution to global poverty.

# Table of Contents

# I. Introduction

The alleviation of poverty in the developing world is one of the most difficult challenges faced by the development community today. It has been proven that the accumulation of human capital is an effective and indispensable part of the long-term plan to attain this goal, a fact underlined by the inclusion of universal education in the 2015 Millennium Development Goals put forth by the United Nations. In efforts to ameliorate the welfare and the quality of life of the next generation in developing countries human capital formation through increased access to education in rural areas of developing countries is and will continue to be an invaluable and pivotal component. In recent years, microfinance has been presented and integrated into aid programs as an effective way to address this widespread shortcoming of impoverished nations. This paper will attempt to address the validity of this claim that the use of microfinance loans by a household is correlated with increased attendance in school, finding through econometric analysis that such a relationship is not supported.

The data used in this paper is from a survey of households conducted from 1997 to 2007 in several regions of rural Thailand organized by the Townsend Thai project and collected by the Thai Family Research Project. Regression models are used to assess any measurable correlation between children's years of schooling and microfinance loans within households when other observable traits are held constant. Explanatory variables include individual (age, gender, years of schooling completed) and household (net income, profit estimates for following year, number of microfinance loans) components.

The findings of this paper stand in stark contrast to claims made as to the implications of microfinance loans for children's educational attainment. Using the longest running panel data to date that has been collected in a developing nation, no statistically significant correlation between number of loans and enrollment in school can be found. Despite numerous variations of the explanatory variables included in the regression equations, the correlation never ceases to be insignificant, implying that microfinance, contrary to popular belief, may not be an overarching working solution to global poverty. The policy and program implications of these findings are monumental as the total loan volume is on the rise. In 2001, it totaled and estimated $4 billion and jumped to $25 billion in 2006.[1] These funds may prove to be more cost effective in their aims to increase human capital formation in the developing world if they were, at least in part, directed elsewhere.

## II. Background

It has been long since recognized that the creation of human capital is an effective tool for reducing poverty in the long run. This experiment has been duplicated many times first by Schultz (1961), again by Kreuger and Lindal (2000), and again with Bils and Klenov (2000). The practical question is how best to stimulate the formation of human capital in regions that are already poor in infrastructure and resources. Given the labor-supply potential of children, a poor household faces a higher opportunity cost to sending their child to school. Thus, one

[1] See Dieckmann, R. 2007.

expects that income levels will positively influence a household's schooling decision, whilst negative income shocks will have the opposite effect.

In a study done by Behrman and Knowles (1999) they show that "the stronger are the associations between household income and child schooling, the lower is intergenerational social mobility and the less equal is opportunity." This is one channel through which researchers claim microfinance may influence children's educational attainment and, therefore, human capital formation. "One of the first things poor people all over the world do with new income from microenterprise is invest in their children's education. Studies show that children of microfinance clients are more likely to go to school and stay in school longer. Student drop-out rates are much lower in microfinance client households" (Littlefield et al, 2003). In a joint study by BIDS and World Bank in Bangladesh, findings supported the claim that micro-finance programs promote the poor household's investment in human capital through schooling and the contraceptive behavior of families (Khandker 1998, Pitt and Khandker, 1998).

Microfinance has captured the imagination of academics, policymakers, and practitioners, and it has demonstrated its effectiveness in lending to poor households and alleviating some financial pressures. However, microfinance has expanded its reach beyond the financial world, becoming an important part of development and aid programs. There have been several papers published in the recent past that attempt to assess how apt microfinance programs are at alleviating poverty on a larger scale and over the long run. One such paper, entitled "The miracle of microfinance? Evidence from a randomized evaluation" by Banerjee et al.,

finds ambiguous results as to the long run impact of microfinance programs. One the one hand, there is the possibility that those who take out loans cut back on consumption in the current time period in order to allow for greater investment and reap the benefits of higher income and increased consumption in the future. However, it may also be the case that borrowers increase their consumption upon receiving the loan rather than using it for investment, in which case he/she is borrowing against his/her future in hopes that their economic situation will better itself. In addition to these uncertain long-term effects, the study found that microcredit had no discernible effect on education, health, or women's empowerment. The results of Karlan and Zinman's working paper on expanding credit access lead to similar conclusions, further reinforcing the validity of the claim that microcredit has no observable effect on education.

Focusing on the potential effects of microfinance on children's educational attainment, Holvoet (2004) published an article exploring the influence of the gender of the borrower on the impact of microfinance programs on children's education. Comparing data on various credit programs operational in South India, Holvoet concluded that, in the case of direct bank-borrower credit, the gender of the borrower has no impact on their children's education. Further, Holvoet states that results from regression analysis even suggest that direct individual bank-borrower lending does not induce any effects at all on children's educational inputs and outputs.

Thus, the purpose of this paper is to explore the relationship between microfinance programs and the educational attainment of the children of loan-

holding households in order to assess the true impact of microfinance programs on extra-financial factors that may contribute to the alleviation of poverty through the creation of human capital, namely education.

## III. Data

The data set analyzed in this paper is the derived from panel data collected by the Townsend Thai Project between 1997 and 2007 in the Buriram, Chaochoengsao, Lop Buri, Petchabun, Phrae, Satun, Sisaket, and Yala provinces of Thailand. Including 15 households in each of 64 villages distributed across the provinces, the data gathers a random sample that is both stratified and clustered. The average attrition rate from year to year was 3% and was largely due to migration. Thus, of the 960 households that were initially surveyed, 800 of them were resurveyed for the first seven years and 655 of them were followed by the study for all eleven years. With such a low rate of attrition, the data provides an excellent estimate of the average trends of a household across time.

The data set used in this paper was created by extracting relevant variables from the Townsend Thai Data, which consist of the following: current enrollment in school (sch), number of years of schooling the child has completed (yrsch), gender of the child (male), number of microfinance loans the family has (numloans), household net income of the family (netinc), household profit estimates for the following year (profest). The variables for current enrollment in school and gender are both binary variables. The data for these various variables was then aggregated across all eleven years to create a succinct package of key variables that could be

used to study the impact of microfinance loans on the educational attainment of the children of the various households surveyed.

After the data set was compiled from the source, it was analyzed using STATA. Before any tests were done on the data, summary statistics were obtained for each variable, which can be seen in Table 1 of the appendix of this paper. It is interesting to note that the average number loans per household is 1.76 with a standard deviation of 1.55, so over half of households in the survey have at least one microfinance loan and most have no more than three or four. Therefore, the number of observations is more than sufficiently large to give a good estimate of whether the effects of taking out the first loan or jumping from the first to the second loan or from the second to the third loan is statistically significant. Further, one should note that the average age of the children in the survey is about 11 and the children are approximately 52% male, so the analysis will give a good measure of the effects for school age children and show the differences across gender.

## IV. Empirical Models and Econometrics

When parents decide as to whether or not their children will attend school, the choice is largely one about income allocation. A particular household's demand for education depends not only upon their preferences but also upon their financial situation. It may be to the economic advantage of the family that the child allocates his or her to time to work either in the household or in the labor market. Availability of microcredit may therefore influence a household's educational decisions through consumption smoothing, risk reduction, or increased productivity.

Children may be more likely to attend school should a microfinance loan smooth consumption by alleviate financial pressures causing the parents to keep their child(ren) out of school to contribute to household earnings. It could also serve to reduce risk by giving households another source of funding should other economic endeavors fail or prove to be unfruitful. This would make a child of such a household more likely to attend school, as there is more disposable income that can be allocated to education as opposed to being used for insurance purposes. On the other hand, a child may be less likely to attend school if a microfinance loan causes the parents to allocate more time to their professional endeavors, increasing the productivity of their business and transferring responsibility for the household duties to one or more of the children. Finally, microfinance could prove to have no effect whatsoever should households already be consuming their optimal amount of schooling, should preferences dictate that disposable income is allocated to education with low priority. Thus, parents are choosing the amount of schooling that maximizes their utility over the long run according their perceived profitability of education.

In order to determine whether or not taking out microfinance loans has any effect of children's educational attainment, linear models were created with a dummy variable for whether or not the child is enrolled in school as the dependent variable. The final model includes all of the observable factors for which data was available that one might expect could influent a child's educational attainment. The independent variables in this final model are number of loans, age, gender, years of previous schooling, and net income. Age is included, because the older the child is,

the less likely that child is to attend school. Gender is controlled for so as to control for any systematic preference as to which children are educated. Also included is years of schooling, because a child is more likely to attend school if they have consistently done so in the past and less likely to attend once they have reached a certain grade-level. Finally, net income is controlled for in order to eliminate any effects of wealth disparity on a child's likelihood to be educated, and profit estimates for the next year are held constant to control for any effect expectations for the future may have on household decisions about income allocation and thereby schooling.

The linear regressions used in this study were largely run looking at the individual fixed effects in order to control for any household preferences or unobservable traits that may influence the decision whether or not to enroll their child(ren) in school. Running a model with individual fixed effects means that the data for each individual is compared to itself across time periods, resulting in an aggregate trend for the society that is determined by the average of all the individual trends as opposed to the trend of the population average. Therefore, we can map the changes in the overall tendencies independently of the varying unobservable traits each individual may have or be subject to and control for them, thus relying only on the measurable data available.

The first linear regression that was run in order to obtain OLS estimates was

$$(1)\ sch = \alpha + \beta * numloan + \varepsilon.$$

This regression was run looking at the individual fixed effects, thus tracing the relationship between a household's fluctuation in quantity of microfinance loans

and the changes in school attendance for a particular child within that household. The estimate for the coefficient of numloan was -0.002, showing that there is a very small negative relationship between the number of microfinance loans a household has and their children's enrollment in school. However, these results prove to be statistically insignificant as the t-stat is 0.95. Further, the explanatory power of this regression, expressed by the value of R-squared, is quite weak, and, thus, it does not explain much of the variation in school enrollment. The value of R-squared here is 0.0005, implying that only 0.05% of the variation in the dependent variable can be explained by number of microfinance loans alone. These results suggest that there may be omitted variable bias, a phenomenon that may account for the lack of statistical significance of the coefficient for numloan.

To further analyze the individual effects of each additional loan, the following linear regression was run:

$$(2)\ sch = \alpha + \beta*numloan\_1 + \gamma*numloan\_2 + \phi*numloan\_3 + \delta*numloan\_4 + \xi*numloan\_5 + \lambda*numloan\_6 + \eta*numloan\_7 + \zeta*numloan\_8 + \mu* numloan\_9 + \varepsilon$$

Here, each number of possible loans is run as its own dummy variable so as to determine if any particular additional loan taken out has a greater impact than the others. In this regression we also look at the individual fixed effects, which shows how a change over time in number of loans within a particular household affects each child within said household. However, the results of regression show that none of the coefficients are statistically significant at the 95% confidence level, thus reinforcing the result of equation (1) that there is no correlation present between

enrollment in schooling and number of loans alone and that we may be dealing with omitted variables bias.

In this next regression, an interaction term for number of microfinance loans and gender is run as the explanatory variable in an attempt to determine whether an additional microfinance loan has a different effect on enrollment in school for each gender:

$$(3)\ sch = \alpha + \beta*numloan*male + \varepsilon.$$

The estimated coefficient for numloan*male is slightly negative but proves not to be statistically significant with a t-stat of 0.88. This suggests that the influence of a change in the number of loans on the decision as to whether or not to enroll a child in school does not vary across gender. Thus, a microfinance loan has generally the same overall effect on enrollment for each gender, and including this interaction term in subsequent regressions would not provide any additional information that is not already shown by the coefficients estimates for numloan and male as they stand alone.

In order to eliminate the bias, a third regression was run with the addition of the age and years of previous schooling explanatory variables:

$$(4)\ sch = \alpha + \beta*numloan + \gamma*age + \delta*male + \lambda*yrsch + \varepsilon.$$

The results of this regression appear staggering. The coefficient for numloan is -0.008 and has a t-stat of 4.25. Therefore, it would appear that adding these explanatory variables eliminated the omitted variable bias and revealed a weak and, interestingly, negative correlation of number of microfinance loans with children's educational attainment. However, when the model is rerun while looking at the

individual fixed effects the coefficient on numloan loses its statistical significance as the t-stat fall below 2. Thus, the results lead once again to the conclusion that there is, in fact, no correlation between microfinance loans and school enrollment. Here, age and years of schooling do prove to be very statistically significant with age being strongly negatively correlated and years of schooling having a strong positive correlation with the dependent variable. This speaks to the cultural tendencies of the society. Older children are less likely to be enrolled in school, suggesting that higher education is not highly valued in comparison to a child's ability to financially contribute to the family income. However, the longer a child is in school, the more likely he/she is to stay in school.

In the next set of models variables are included for household net income, profit estimates for the next time period, and log of net income. In the first of such regression models we look at the individual fixed effects with only the addition of net income and profit estimates:

(5) $sch = \alpha + \beta*numloan + \gamma*age + \delta*male + \lambda*yrsch + \eta*netinc + \phi*profest + \varepsilon.$

The new coefficient estimate for numloan under this model is still slightly negative and the t-stat continues to be quite low, rendering the estimate statistically insignificant despite controlling for the financial figures. While the coefficients for age and yrsch have not fluctuated in any meaningful measure and are still statistically significant, those for netinc and profest are statistically insignificant. As we are looking at the individual fixed effects, this implies that income and expectation of future income is uncorrelated with a household's educational decisions.

In an effort to find some correlation a final linear regression model was run that included the log of household net income:

(6) $sch = \alpha + \beta*numloan + \gamma*age + \delta*male + \lambda*yrsch + \eta*netinc + \phi*profest + \mu*lognetinc + \varepsilon.$

Again looking at the individual fixed effects, the slightly negative coefficient estimate for numloan is statistically insignificant and no correlation is found. Interestingly, the coefficient estimate for the log of household net income is statistically insignificant as well, suggesting that fluctuations, as well as the nominal value, of the income of a household are uncorrelated with the school enrollment of the children in said household.

In addition, residuals were obtained for the following two regressions:

(7) $sch = \alpha + + \gamma*age + \delta*male + \lambda*yrsch + \eta*netinc + \phi*profest + \mu*lognetinc + \varepsilon.$

(8) $numloan = \alpha + \gamma*age + \delta*male + \lambda*yrsch + \eta*netinc + \phi*profest + \mu*lognetinc + \varepsilon.$

Model (7) is a regression of the current enrollment status of the child on the explanatory variables, excluding numloan, and model (8) is a similar regression with numloan as the dependent variable. The residuals from these two regressions were obtained and compared with one another on a scatter plot where the residuals for the number of microfinance loans is on the horizontal axis and the residuals for the child's current enrollment status is on the vertical axis. The graph, depicted in Figure 1 in the appendix, shows a very slight negative correlation between the two sets of residuals, but the linear fit line is essentially zero. Thus, we have yet another illustration of the lack of correlation between the number of loans a household holds and the enrollment status of the children of that household in school.

## V. Ruling out Exogeneity

Granted, problems of exogeneity could account for this lack of correlation between number of microfinance loans and children's enrollment status in school should there be exogenous shocks that influence the composition of the population of loan holders as well as the likelihood that a child will attend school. Here, income and health shocks are identified as the two main channels through which exogeneity may be caused.

An income shock would certainly make a child less likely to attend school, as, relatively, the opportunity cost of forgoing the additional income they could contribute to the household would be larger. Income shocks, lowering disposable income, may also make it more likely that a household applies for a microfinance loan in order to bridge this gap. Accounting for such unexpected changes in income is rather overarching as in rural societies income is directly influenced by soil and weather conditions, economic conditions, and productivity.

Regressing number of microfinance loans on net income from the previous period, one can assess whether or not an income shock was the cause of exogeneity through examining its relationship with borrowing behavior.

$$(9)\ \text{numloan} = \alpha + \beta * \text{lastnetinc} + \varepsilon.$$

The coefficient estimate for the preceding year's net income is not statistically significant, and therefore we can rule out any existence of exogeneity due to an income shock. The results of this regression are displayed in Table 4 of the appendix.

A health shock is another phenomenon that could potentially cause exogeneity, as it may be correlated both with school attendance and borrowing tendencies. A child becomes much less likely to attend school should he/she have an illness or should there be an illness in the family, because they may be physically unable to attend or they may be required to work in the stead of a sick parent or family member to maintain the family's level of income. Likewise, a health shock may increase the likelihood that a household would apply for a microfinance loan, because they may not have the funds necessary to pay for medicines and/or treatment without a loan or they may not be able to maintain a subsistence level of income and, thus, need a microfinance loan to stay afloat.

In order to fully assess the potential impacts of a health shock on the number of microfinance loans a households has, the data set would need to include data on a household's health status or expenditure on health. Ideally, a variable for log of healthcare expenditures would be included, measuring the percentage deviation in expenditure on health from the previous time period. This would show whether or not a much larger amount of a household's income was spent on health than in the previous year. This would, in turn, expose the existence and extent of a health shock. By regressing the log of healthcare expenditures on the number of microfinance loans, one would be able determine whether or not a health shock lead to exogeneity and, possibly, rule it out.

An income shock is likely the more important of these two possible sources of exogeneity, as the choice as to whether or not to enroll a child in school is largely one about income allocation. By ruling it out, one can be fairly confident that the

results of the data analysis presented in this paper are valid and the number of microfinance loans a family has incites no change in whether or not their child or children are enrolled in school.

## VI. Policy Implications

The potential policy implications of these findings are substantial. More than $25 billion is doled out in microfinance loans each year to poor and impoverished individuals around the world. While this money is important for those household's immediate needs and/or investment in physical capital, these sums would make a much more significant impact on the economies of these developing countries in the long term and the projected incomes of the next generation if at least some part of each loan was serving to facilitate the creation of human capital, namely education. Having a more educated population would mean having a more productive work force that is capable of performing jobs requiring higher skill level, in turn creating a market that would attract foreign investors and increase exports.

Borrowers in developing countries ought to be allotting a larger proportion of their loans to human capital formation in order to raise the standard of living for the next generation and escape the poverty trap. One solution to this shortcoming is to institute a convention of adding a conditional cash transfer clause to lending agreements that conditions the transaction on the behavior of the borrower with respect to investment in human capital (education, health, nutrition). This would essentially force a relationship between number of microfinance loans and children's enrollment status in school.

In addition to modifying the lending agreements of microfinance programs, it may be even more effective to also facilitate asset building for the poor. This may be by means of policies and initiatives that expand access to saving and other financial services such as insurance, allowing households to make more sophisticated and less risky investments in their human as well as physical capital. Having a decent amount of savings allows a poor household to build their own assets and self-insure them against risk and/or possible shocks.

The amount of money required for a family in a developing nation to rise out of poverty enough to send their child to school may, however, rest at quite a high threshold, and any sum of money borrowed below this threshold may have no effect on children's education if the family has not yet reached the level of subsistence necessary to send their child to school, a relative luxury. Thus, it may be the case that the majority of microfinance loans do not constitute a large enough sum to outweigh the opportunity cost of forgoing the additional household income contributed by a child's participation in household chores, the family business, or the labor market. This would imply that only loans of some threshold amount that varies across households would have an effect on children's educational attainment, and any loan that falls below would not display any effect.

These smaller loans may, however, have some effect on children's educational attainment, but these results may only be seen across a much longer time period. That is to say that the effects a microfinance loan has on the household income may take several years to manifest, and it is, therefore, only after this time period has passed that the household would have the financial ability to send one or

more of their children to school. In sum, a larger sum of money would be more likely to yield more instantaneous results whereas the impact of a smaller sum of money may require a longer period of time to manifest, if it all.

## VII. Conclusion

With the extent of poverty across the developing world, implementing policies and programs aimed at raising the standard of living and breaking the vicious cycle of poverty traps is becoming a higher priority. One such mechanism is to increase the rate of human capital formation, which will simultaneously raise the expected income of the next generation and increase productivity of the labor force. Perhaps the most well-known and universal ways to generate human capital is through education. Thus, by measuring the levels of educational attainment in a country one can estimate its average standard of living, where higher educational attainment reflect a higher standard of living.

One of the most relevant research questions is, therefore, how best to stimulate and support the formation of human capital via education. With the rising popularity of microfinance programs in the public and private spheres, it is important to determine to what extent microfinance loans affect a household's behavior with respect to education and whether or not it is an effective tool to fight poverty.

When analyzing the impact of microfinance loans over the long run, one finds no effect on the educational attainment of children. A child is neither more nor less likely to be enrolled in school in any given year when the number of microfinance

loans held by their family increases. Therefore, it is clear that microfinance programs, as they are now organized, are not in and of themselves a mechanism through which the creation of human capital can be stimulated so as to increase the standard of living. However, should the allocation of some funding to education be built into the loan agreement, one might find very different results as to the impact each loan has on enrollment. Be that as it may, the evidence analyzed here from rural Thailand shows that microfinance programs to date have no impact on children's educational attainment.

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# Appendix

**Table 1: Summary Statistics of Key Variables**

| Variable | Mean | Median | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Numloan | 1.76 | 1.00 | 1.55 | 0.00 | 9.00 |
| Age | 11.04 | 11.00 | 3.95 | 1.00 | 18.00 |
| Male | 0.53 | 1.00 | 0.50 | 0.00 | 1.00 |
| Netinc | 144828.70 | 63400 | 1990000 | 854000 | 117000000 |
| Profest | 494000000 | 60000.00 | 6990000000 | -400000 | 100000000000 |

**Table 2: OLS Regression Results Part 1**

Dependent Variable: Child's current enrollment status in school

| **Explanatory Variables** | **(1)** | **(4)** | | **(5)** | | **(6)** | |
|---|---|---|---|---|---|---|---|
| | | Females | Males | Females | Males | Females | Males |
| Numloan | -0.002 | -0.002 | -0.004 | -0.002 | -0.005 | -0.003 | -0.004 |
| | (0.95) | (0.51) | (1.20) | (0.43) | (1.2) | (0.65) | (1.01) |
| Age | | -0.022 | -0.057 | -0.034 | -0.058 | -0.022 | -0.058 |
| | | (4.53)** | (11.98)** | (4.58)** | (11.58)** | (4.22)** | (11.51)** |
| Yrsch | | 0.020 | 0.047 | 0.021 | 0.047 | 0.020 | 0.048 |
| | | (5.37)** | (12.19)** | (5.23)** | (11.63)** | (5.00)** | (11.68)** |
| Netinc | | | | 0.000 | -0.000 | 0.000 | -0.000 |
| | | | | (0.44) | (0.72) | (1.15) | (0.87) |
| Profest | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| | | | | (1.05) | (0.79) | (1.15) | (0/87) |
| Lognetinc | | | | | | -0.002 | -0.009 |
| | | | | | | (0.24) | (1.27) |
| Constant | 0.851 | 0.958 | 1.112 | 0.971 | 1.129 | 0.979 | 1.226 |
| | (167.30)** | (31.12)** | (39.55)** | (30.66)** | (37.97)** | (12.66)** | (15.44)** |
| R-squared | 0.00 | 0.01 | 0.03 | 0.01 | 0.03 | 0.01 | 0.03 |
| Observations | 14538 | 6874 | 7664 | 6469 | 7172 | 6398 | 7111 |

Absolute value of t-statistics in parentheses * significant at 5% level; ** significant at 1% level

**Table 3: OLS Regression Results Part 2**

| Dependent Variable: Child's current enrollment status in school | | |
|---|---|---|
| **Explanatory Variable** | **(2)** | **(3)** |
| Netinc*male | -0.000 | |
| | (0.88) | |
| Numloan_1 | | -0.002 |
| | | (0.20) |
| Numloan_2 | | -0.013 |
| | | (1.07) |
| Numloan_3 | | 0.002 |
| | | (0.13) |
| Numloan_4 | | -0.016 |
| | | (1.00) |
| Numloan_5 | | -0.009 |
| | | (0.49) |
| Numloan_6 | | -0.055 |
| | | (1.96) |
| Numloan_7 | | -0.014 |
| | | (0.39) |
| Numloan_8 | | -0.088 |
| | | (1.70) |
| Numloan_9 | | 0.086 |
| | | (1.58) |
| Constant | 0.848 | 0.852 |
| | (325.51)** | (99.49)** |
| R-squares | 0.00 | 0.00 |
| Observations | 14089 | 14538 |

Absolute value of t-statistics in parentheses
* significant at 5% level; ** significant at 1% level

**Table 4: Income Shocks OLS Regression Results**

| Dependent Variable: Number of microfinance loans | |
|---|---|
| **Explanatory Variable** | **(9)** |
| Lastnetinc | -0.000 |
| | (0.65) |
| Constant | 2.020 |
| | (102.46)** |
| R-squares | 0.00 |
| Observations | 8292 |

Absolute value of t-statistics in parentheses
* significant at 5% level; ** significant at 1% level

Figure 1: Residual Plot

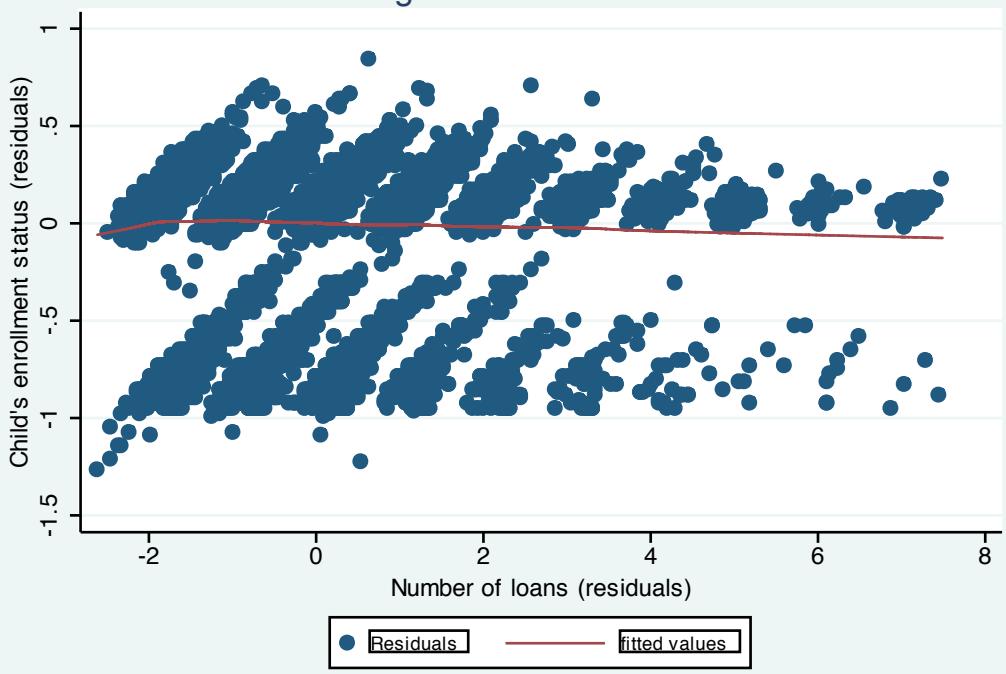


Figure 2: Impact of Number of Loans on Enrollment Status