Credit Crisis and Human Capital: Evidence from Micro-Finance Regulation in India

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October 5, 2022

Abstract

A large emergent literature highlights that wage-reducing economic shocks can have ambiguous effects on human capital accumulation. In our study, we theoretically propose and empirically establish that these effects are not homogeneous on children in all grades in the presence of dynamic complementarity in education. We utilize a 2010 micro-credit finance ban in Andhra Pradesh, India, that halted all micro-credit operations impacting loan recovery and liquidity in the state, to test our theory empirically in a synthetic differences-in-differences framework. We find an overall reduction in school enrolment of 6 percentage points due to the ban. However, this is driven by children in primary, middle, and secondary school. In sharp contrast, higher secondary school enrollment increased. This strategic behavior of the households is borne out in child labor decisions as well: younger children's likelihood of participating in wage-earning activities increased, while that of older ones fell.

Keywords: Human capital, dynamic complimentarity in education, Child Labor, Micro-Credit

JEL codes: G21, J13, O15, J21

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1 Introduction

A large literature explores the consequences of changes in wages resulting from economic shocks for human capital and child labor both theoretically and empirically. Theoretically, the effect can go in either direction. An income effect should increase enrollment but at the same time, substitution effect can reduce it. Empirically, the effect depends on whether the income effect dominates the substitution effect. The results are mixed (Jacoby and Skoufias, 1997; Jensen, 2000; Thomas et al., 2004; Maccini and Yang, 2009) but studies have also found the opposite (Hossain, 2022; Shah and Steinberg, 2021; Li and Sekhri, 2020; Edmonds and Theoharides, 2020; Shah and Steinberg, 2021).

However, this literature assumes that households treat each child's human capital the same. In the presence of dynamic complementarities in education (Cunha and Heckman, 2007), this may not be true. In rural areas of developing countries, majority households have more than one child. For example, as per a recent survey in India, 59% of households had more than one school-aged children. Consequently, parents may not make the same choices for each child when faced with a shock to wages. While an improvement in wages can have income and substitution effects in opposite directions, tightening of credit typically lowers demand for labor. Thus, these countervailing effects may not arise. In this paper, we propose a model that takes into account dynamic complementarity in education and address the consequences credit constraints by birth order of children.

We develop a simple two-period model of family's strategic investment in child education and labor. In the model, households maximized utility derived from consumption and children's human capital enters into the budget constraints. We incorporate dynamic complementarities in education such that previous investment in education makes current investment more productive (Cunha and Heckman, 2007). The model yields two testable predictions about strategic investments of parents in children's education in times of a credit crisis. First, younger aged children are more likely to dropout of schools due to lower future expected return and vice versa. Second, in a household with more than one school-aged children, elder siblings are more likely to stay in schools, while younger siblings are more likely to work to compensate for the loss of income.

To empirically test the implications of our model, we exploit a ban on microfinance activities in the state of Andhra Pradesh that ushered a microfinance crisis in the state. In 2010, an ordinance by the state of Andhra Pradesh, India, brought to a complete halt all operations of all the private microfinance organizations in the state, adversely affecting their loan recovery and liquidity. This contracted the credit supply available to poorer rural households

by a large magnitude. Breza and Kinnan (2021) examine the general equilibrium effects of this credit supply shock and show that the shock led to a substantial decline in casual wages and wage earnings. We study this episode of steep reduction in credit supply on children's human capital attainment and labor supply. The novelty of this paper is two-fold: One, prior studies exploring the relationship between microfinance and human capital investment exploit the variation from the expansion of credit. To the best of our knowledge, this is the first study examining the effect of a ban on microfinance on human capital attainment. In this case, both the income and the substitution effects go in the same direction. Two, prior studies examine the average effect of the income shocks, ignoring that children of different ages might be affected differently. We focus on consequences for children at different levels of education ladder and age.

In 2000's, micro-credit was rapidly expanding in India's poor regions. In 2008, 208 out of 640 districts, shown in Appendix Figure C.1, had presence of private micro-credit lending institutions. We collated data from various government sources to ascertain these districts. Our empirical analysis relies on these 208 districts which had micro-credit lending via private institutions including those in ban affected state of Andra Pradesh. For our empirical analysis, we link the microfinance exposure data with three other sources of data. To examine the effect on school enrollment of children, we use the *Annual State of Education Report (ASER)* survey data. To explore the effect on labor force participation, we use the *National Sample Survey Organization (NSSO)* data. Finally, to shed light on the mechanisms at the household level, we use household panel data from the two rounds of the *India Human Development Survey (IHDS)*. [1]

Our identification approach leverages the comparison of the MFI districts in Andhra Pradesh (treated districts) with the MFI districts from the other states (control districts) before and after the micro-finance ban in 2010. An event study analysis reveals that all the exposed districts pooled together are not a good counterfactual to the districts in Andhra Pradesh due to differential pre-trends. In order to circumvent this issue, we utilize a synthetic differences-in-differences Strategy (SDID) proposed by Arkhangelsky et al. (2021). This approach combines the benefits of both the synthetic controls methods (Abadie and Gardeazabal, 2003) and the difference-in-difference strategy and by construction the synthetic control group has parallel pre-trends.

Consistent with our theory, we find that the ban on micro-finance lowered children's school enrollment by six percentage points. Our model's predictions bear out in the data. We find

[1] Refer to this website for more information about the data.

that in case of one-child households, younger the child, more likely is the child to drop out of school. Grade level matters: children in senior secondary schools, for which the documented returns are higher, stay in school, whereas children in secondary, middle and primary are more likely to drop-out. In case of multiple children households, younger children drop out of school and are more likely to work for wages. Older children have a higher likelihood to stay in school. These findings are important from policy perspective. Programs designed to protect children from dropping out of school and entering child labor markets should target younger children especially in the face of credit constraints.[2]

Our paper contributes to the literature exploring the effect of economic shocks induced changes in wages on human capital investment in children. Studies in developing countries explore how child labor and schooling respond to rainfall shocks and document that human capital attainment is often counter-cyclical or exhibits seasonal fluctuation without any real effects on human capital (Shah and Steinberg, 2017; Jacoby and Skoufias, 1997). [3] Financial intermediation in form of large asset transfers (Edmonds and Theoharides, 2020), expansion in agricultural credit (Hossain, 2022), and employment-based safety-net programs (Shah and Steinberg, 2021; Li and Sekhri, 2020) result in a decrease in human capital investment and increase in child labor. On the other hand, several studies demonstrate that adverse shocks reduce human capital (Jensen, 2000; Beegle et al., 2006; Duryea et al., 2007; Gubert and Robilliard, 2008; Björkman-Nyqvist, 2013) (Skoufiou and Parker, 2006). These repercussions are often construed as a test of credit market imperfections as income shocks would not affect schooling if there were no financial market imperfections and households could borrow without constraints.[4] We complement this literature by demonstrating that credit constraints do not affect all children equally. Unlike these previous papers on credit expansion, we use a ban on micro-credit as a source of variation which should unambiguously reduce enrolment but we find differences in the effects across grades that children are in. Shah and Steinberg (2017) demonstrate heterogeneity in the effect of rainfall shocks on human capital by age and find that positive rainfall shocks in utero to ages 2, have a positive effect on human capital but such shocks have a negative effect after age 5. This stems from time and income both being inputs in human capital production. In contrast, we find that for school- aged children, older children are less likely to drop out of school, whereas younger

[2]In the long run, experience in child labor can improve labor market outcomes, but human capital benefits outweigh the experience.

[3]Counter-cyclicality is demonstrated in the US as well. Cascio and Narayan (2022) demonstrate that economic booms resulting from increased fracking in the United States increased high school dropout rates due to an increase in the demand for unskilled labor.

[4]Poor and disadvantaged plausibly face similar circumstances in developed countries. Adverse economic shocks affect human capital for disadvantaged children in developed countries too (Page et al., 2009) (Coelli, 2011).

children are more likely to drop out. We attribute this to dynamic complimentarity in education, increasing returns to education, and forward looking behavior by the households.[5]

A large body of work also examines the consequences of micro-credit lending for schooling outcomes and finds mixed results (See USAID review for details). Our study departs from the existing micro-credit interventions in several regards. First, our setting is different with respect to the magnitude and scale. The AP micro-credit shock was enormous in nature that affected the entire districts encompassing whole labor market. This was also a supply shock without any demand changes. Hence, we can delineate the effects of credit supply. We also distil evidence of differential effects for different grade levels.

The rest of the paper is organized as follows: Section 2 describes the study setting. Section 3 discusses the conceptual framework. Section 4 describes the data. Section 5 outlines the empirical methodology to estimate the impact of micro-finance ban on human capital attainment and labor supply of children. Section 6 discusses the results and describes the potential mechanism. Section 8 concludes the paper.

2 Background

2.1 Microfinance in India

Microfinance plays an important role in the development of India. It aims to foster financial inclusion of the poor and alleviate poverty. In 1992, the first modern microfinance program, the Self-Help Group-Bank Linkage programme (SBLP), was launched by National Bank for Agriculture and Rural Development (NABARD). Under this program, banks directly finance SHG and NABARD refinances bank loans. Another major credit delivery channel is the MFI model, which grew rapidly in the late 1990s and the 2000s. MFIs are heterogeneous ranging from not-for-profit societies, trusts, and organizations to for-profit non-banking financial companies (NBFCs) and local banks. The MFI is one of the most popular options for households to meet their credit needs. In 2008, while 36 million people were included under the SBLP, only 20% of them borrowed. Yet, about 11.9 million out of 14 million people outreached by MFIs were borrowers of microcredit.[6]

[5](Foster and Gehrke, 2017) model human capital investments in response to ex ante risk and build in dynamic complimentary in education.

[6]Data is from this report. For more details about the history of microfinance in India: Sinha (2009).

Most of the microfinance services are concentrated in South India. Saraf (2015) finds that the presence of MFIs is positively correlated with local economic development and the historical background in the Southern region makes the concept of microfinance more permeable. We plot the distribution of MFIs across districts in 2008 in Appendix Figure C.1. It can be seen that districts in the northern regions are less likely to have an MFI. We use the 2011 Census of India to test if districts not having MFIs are significantly different from districts having MFIs. As shown in Appendix Table C.1, districts that have MFIs tend to have more people, more households, and more males.

2.2 2010 Microfinance Crisis in Andhra Pradesh

Microfinance was hot in the late 2000s. About 85% of a survey's respondents in Andhra Pradesh (AP) borrowed money from MFIs in 2009 (Ghiyazuddin and Gupta, 2012). By September 2010, the MFIs had over INR 72 billion outstanding loans in AP and each borrower on average had a debt of $300, which was 45% higher than the amount of debt held by an SBLP member (Sriram, 2012). MFIs have been criticized for their nontransparent and high interest rates (i.e. ranging from 50% to 84%[7]) and coercive collection practices (i.e. doorstep loan management) for a long time. More than 80 people committed suicide after defaulting on micro-loans in 2010, which urged the state government to take action over MFIs.[8]

On October 15, 2010, the government of Andhra Pradesh unexpectedly issued an emergency ordinance to regulate money lending of MFIs in response to the rising committed suicide cases and public outcry in the state.[9] The ordinance brought a complete halt to MFI's activities. It prohibited the doorstep collection of loans and barred MFI from giving new loans in Andhra Pradesh. With most borrowers refusing to repay their MFIs loans, the outstanding loans amounted to INR 72 billion in Andhra Pradesh. The banks which previously funded MFIs stopped lending money to MFIs due to the concern of mass default. As a result, MFIs located outsides Andhra Pradesh also contracted their activities temporarily.

[7] Data is from this website.
[8] Data is from *India's Micro-Finance Suicide Epidemic* published by BBC in December 2010.
[9] For more details about the crisis: Sriram (2012); Mader (2013).

3 Theoretical Framework

In this section, we describe a simple two-period model of the joint household decision on child labor and schooling. In the presence of credit shocks, households decide if they will send the child to work based on one's expected income in the adult period and in the child period.[10] The model provides us with testable predictions that we will bring to the data.

3.1 Setup

The decision-maker of a household is the parent. The parent supplies labor inelastically, earning an income of w_p, in each period. The parent can also borrow money, $b \leq A$ where $A > 0$, in a well-functioning credit market in the first period (or period I). It should be noticed that in the presence of MFI ban, we have $A = 0$.[11] In period I, the parent decides if they want to educate a child at a cost of e_i, where i is a subscript for child i, and the extent to which a child will work, $t_i \in [0,1]$. Education cost e_i is defined as $e_i = v(1-t_i)$ where $0 < v < 1$.[12] A child will then spend $1-t_i$ time on study. There are three cases for t_i: 1) $t_i = 0$, the child's time is used only in schooling; 2) $t_i = 1$, the child's time is used only as labor supply; 3) $t_i \in (0,1)$, the child share his time between work and schooling. If a child works in period I, then s/he earns $w_c t_i$, which can be entirely used by the parent. We assume that $w_p \gg w_c \geq 1$.

In the second period (or period II), the child becomes an adult. S/he will supply one unit of labor and earns an income of $w_c h_i$, where h_i is child i's human capital accumulated in period I. We define $h_i = h(t_i) = \gamma \exp(g_i(1-t_i))$,[13] where γ is a technology constant, with $h(1) = \gamma > 0$. We define $g_1 > g_2 = dg_1 > ... > g_N$ with $0 < d < 1$. We have $\frac{\partial h_i}{\partial t_i} < 0$, which implies that a child's human capital is decreasing in his/her working hours in period I. $\frac{\partial h_i}{\partial g_i} > 0$ suggests that a child's human capital is increasing in a child's grade. We also have $\frac{\partial^2 h_i}{\partial g_i^2} > 0$, which is consistent with dynamic complementarities arguing that early educational investment in human capital make the current investment more productive (Cunha and Heckman, 2007).[14]

[10] This is a partial equilibrium model. We abstract away from the changes in wages.

[11] It is true that households can still borrow money from other sources such as money lenders which usually have a higher interest rate. Here, we simply assume that household cannot borrow money.

[12] v can be thought as an indicator of ability. The smaller the v is, the more able a child is. Testing children's ability is out of the reach of this paper.

[13] In Soares et al. (2012), they assume an exponential form of human capital function for children. Here, we assume that a child's human capital is increasing in both one's grade and time spent on schooling.

[14] A number of studies in different countries find that the return to primary education in wage employment is significantly lower than that to post-secondary education (See Colclough et al. (2009) to see a list of 18 such studies). For instance, in India, the return to primary or middle schooling is at most 7 percent, while

3.2 Households with One Child

A household with only one child solves the following maximization problem in deciding whether to put the child to work or not,[15]

$$\max_{c_I, c_{II}, t_1} U(c_I, c_{II}) = u_I(c_I) + \beta u_{II}(c_{II}), \tag{1}$$

$$\text{s.t. } c_I + e \leq w_p + b + w_c t, \tag{2}$$

$$c_{II} + (1+r)b \leq w_p + w_c h, \tag{3}$$

where c_I is the household consumption in period I, c_{II} is the household consumption in period II, $u(c) = \ln(c)$, and β is the discount factor. For simplicity, we assume that $\beta(1+r) = 1$, which means that the household wants to smooth consumption over time and consume at $c_I = c_{II}$. Combining the first- and second-period budget constraints and substituting for e and h, we can write down the lifetime budget constraint for the household:

$$c_I + \frac{c_{II}}{1+r} + v(1-t) \leq w_p + w_c t + \frac{w_p}{1+r} + \frac{w_c}{1+r}\gamma \exp(g(1-t)). \tag{4}$$

The lifetime income constraint is maximized at $t = 0$.[16] The optimal choice for the parent is to borrow money in period I and send the child to a school, $b^* > 0$ and $t^* = 0$.[17]

In the case of MFI ban ($A = 0$), the utility function for a household who is a net borrower in a credit market without the ban becomes:[18]

$$U(t) = \ln\left(w_p + w_c t - v(1-t)\right) + \beta \ln\left(w_p + w_c \gamma \exp(g(1-t))\right). \tag{5}$$

The derivative of equation (5) with respect to t is in Appendix A (equation (17)). The sign of

the return to secondary or higher secondary education is 12.6 percent (Vasudeva-Dutta, 2006). Recent cross-country evidence also suggest that the return to an additional year of schooling increases with the level of education (Schultz, 2004; Kingdon et al., 2008).

[15] In the case of one child, we drop the subscript i.

[16] Here, we assume that the interest rate is not extremely high. In Appendix Figure A.1, we display how the lifetime budget constraint changes with a child's work time when the interest rate is small and when it is large. The cutoff level of interest rate r is $\frac{\gamma w_c(\exp(g)-1)}{v+w_c} - 1$. Assuming that $\gamma = 1, w_c = 1, g = 2, v = 1$, then we have $r_{cutoff} = 3.195$. That is, we will have the lifetime budget constraint maximized at $t = 1$ when the interest rate is larger than 319.5%. Since the case of an extremely high interest rate is uncommon, we assume that r is small (i.e. below the cutoff level) hereafter.

[17] In Appendix Figure A.2, we show that in the case of small r, the household is a net borrower.

[18] There will be no changes if the household is a net saver in the optimal choice with $A > 0$.

the derivative is determined by the numerator which can be written as:

$$\underbrace{(w_c+v)}_{\text{MR to } t \text{ in period I}} \cdot \overbrace{\left[w_p + w_c\gamma e^{g-gt}\right]}^{\text{income in period II}} - \underbrace{\beta w_c \gamma g e^{g-gt}}_{\text{discounted MR in period II}} \cdot \overbrace{\left[w_p + w_c t - v(1-t)\right]}^{\text{income in period I}} \tag{6}$$

$$\Longrightarrow \frac{w_c+v}{w_p+w_c t-v(1-t)} \lesseqgtr \frac{\beta w_c \gamma g e^{g-gt}}{w_p + w_c\gamma e^{g-gt}}. \tag{7}$$

The derivative of the right-hand side in inequality (7) with respect to g is positive for $t \in [0,1]$. So, if the discounted marginal return to education in period II is large or if the child is in a senior grade, then the inequality is likely to be "<" and $\frac{\partial U}{\partial t}$ will be negative. Parents will not send children to work in this case. If the marginal return to child labor is relatively large in period I or if the child is in a junior grade, then the inequality is likely to be ">" and $\frac{\partial U}{\partial t}$ will be positive. That is, the parent will let the child to work to subsidize family income. For g inbetween, it is possible that the inequality has a "=", which suggests that there can be an interior solution to t. We formally write up the propositions derived from the model below.

When a household has *one child* and $A = 0$,

Proposition 1: the parent will make the child work if the child is in a junior grade. The optimal choice with the MFI ban imposed is $t^B = 1 > t^* = 0$. The overall school enrollment for children in the junior grades drops.

Proposition 2: the parent will let the child stay at school if the child is in a senior grade. The optimal choice with the MFI ban imposed is $t^B = t^* = 0$. The overall school enrollment for children in the senior grades is not affected by the ban.

Proposition 3: the elder the child is or the higher the grade a child is in, the more time the parent will let the child work if g is in some range.[19]

3.3 Households with Two Children

In developing countries, it is common for households to have at least two children.[20] We thus extend the model to a household with two children. Parents now also need to determine how to share the education investment between the two children, one elder and one younger.[21]

[19] Proof of proposition 3 is in Appendix A.

[20] The total births per woman were 2.975 in 2005 and 2.581 in 2010 in India according to the World Bank Data.

[21] We do not consider the case of twins here. We assume that the gender of the first child has a neutral impact on a household's decision. We show that this assumption holds in Appendix Table **??**.

Similar to the one-child model, we can also derive the numerator from the derivative of the utility function when the MFI ban is imposed with respect to t_i.[22] The numerator determines the sign of the derivative and can be written as:

$$\overbrace{(w_c+v)}^{\text{MR to } t_i \text{ in period I}} \cdot \overbrace{\left[w_p + w_c\gamma(e^{g_1-g_1t_1}e^{g_2-g_2t_2})\right]}^{\text{income in period II}} - \underbrace{\beta w_c\gamma g_i e^{g_i-g_it_i}}_{\text{discounted MR in period II}} \cdot \underbrace{\left[w_p + w_c(t_1+t_2) - v(2-t_1-t_2)\right]}_{\text{income in period I}} \tag{8}$$

$$\Longrightarrow \frac{w_c+v}{w_p + w_c(t_1+t_2) - v(2-t_1-t_2)} \lessgtr \frac{\beta w_c\gamma g_i e^{g_i-g_it_i}}{w_p + w_c\gamma(e^{g_1-g_1t_1}e^{g_2-g_2t_2})}. \tag{9}$$

Again, the derivative of the right-hand side in inequality (9) with respect to g_i is positive for $t_i \in [0,1]$.

For a given level of g_2, if the discounted marginal return to education for the elder child relative to household income in period II is larger than the marginal return to child labor relative to household income in period I (or the elder child is in a senior grade), then the household will be better off by letting the elder child stay at school. This is because, for each additional unit of investment in the elder child's education, the marginal return to education for the elder child is larger than the return for the younger child as suggested by dynamic complementarities.

For a given level of g_1, the inequality is likely to be ">" if the younger child is in a junior grade and is undetermined if child 2 is sort of child 1's age. In both cases, we have $0 < t_2^B \leq 1$, that is, the younger children will participate in wage-earning activities. Specifically, the younger the child is or the lower the grade a child is in, the more likely the children will drop out of school. Thus, the overall school enrollment will decrease for the younger children.

When a household has *two children* and $A = 0$,
Proposition 4 the parent will let the elder child stay at school if the child is in a senior grade. The overall school enrollment for the elder siblings will not be affected by the ban.
Proposition 5 the parent will let the younger child work to subsidize household income. The overall school enrollment for the younger siblings will decrease.

4 Data

[22] The derivative is in Appendix A equation (26).

4.1 Data on Micro-Finance Institutions

For our empirical analysis, we keep our analysis limited to districts that have at least one micro-finance institution. By the end of 2008, a total of 209 districts of India were served by at least one micro-finance institution. We collect the list of MFI districts from *The Bharat Microfinance Report: Quick Data 2008*, a report compiled by Sa-Dhan.[23] Of these 209 districts, 19 districts were from Andhra Pradesh. These 19 districts form the treated group in our analysis. The rest of the districts serve as the comparison group.

4.2 Data on Child Education

ASER: Our main data source to examine the school enrollment status of the children is the Annual Status of Education Report (ASER) survey. The ASER center sampled households and conducted survey among children aged 3 and 16 every year from 2005 to 2014. This is a nationally representative household survey, covering all the rural districts in India, that collects data on schooling outcome such as enrollment and reading and arithmetic level.[24] There are two distinct features of the ASER survey: One, the sample size is very large, and the sample is representative at the district level, which is the unit of analysis in our main specification. Two, the sample includes all the children aged 3 to 16 irrespective of whether they are currently enrolled or not. We use survey data from 2007 to 2013, restrict data to children aged between 4 and 16, and drop districts that do not have micro-finance institutions. We then collapse the data at the district level and get a district level panel data.

In India, primary schools usually cover grades 1 to 5 for children aged below 10 years old; middle schools cover grades 6 to 8 for 11- to 14-year-old children; and secondary and higher secondary schools cover grades 9 and 10 for children aged between 14 and 16 and grades 11 and 12 for children aged between 16 and 17, respectively. In the data, we categorize students into groups both based on their grades and on their ages.

4.3 Data on Child Labor

NSSO, Employment and Unemployment: The primary sources for data on labor market outcomes are different rounds of National sample Surveys (NSS), which are conducted

[23] See pp 179-186 of the report.

[24] For more details about the ASER sample, see this website.

by National Sample Survey Office (NSSO). National sample Survey (NSS) are nationally representative household surveys that collect data on different indicators of labour force at national and state levels. NSS Surveys are conducted in *rounds*, each round being typically of one-year period and occasionally for a duration of six months. We use the 61st (July 2004-June 2005), 62nd (July 2005-June 2006), 64th (July 2007-June 2008), 66th (July 2009-June 2010), and 68th (July 2011-June 2012) rounds of Employment and Unemployment Survey in our study. We restrict our data to children aged between 4 and 17 for two reasons. First, children usually finish high secondary schools at age 17; second, the 2001 Census of India defines a child less than 17 years old who participate in any economically productive activities as child labor. Similar to the ASER data, we limit our analysis to districts that are covered by at least one micro-finance institution.

IHDS: We use the two waves of India Human Development Survey to explore the effect of microcredit ban on child labor outcomes and to delve into the mechanism. IHDS is a nationally representative survey covering 33 states and union territories, and 384 districts in India. A total of 41,554 households were interviews in the first wave of IHDS (2004-5). A second wave of the survey re-interviewed most of these households in 2011-12 (42,152 households). IHDS collected a wide array of information on different socio-demographic and economic outcomes of the household [25]. We used this two waves of surveys and the census data to construct a panel of children who were aged below 11 years old in the first wave over time. In total, we have 6,507 households and 13,113 school-aged children in the analysis sample. 72% of the households resided in the rural area. The average (median) number of school-aged children in a household has is 2.4 (2). About 45.5% of the households have only one school-aged child. Among the households who have more than one school-aged children, the average number of school-aged children is 2.8.

5 Empirical Strategy

In this section, we describe our identification approach for estimating the effect of Andhra Pradesh's microcredit ban on children's schooling and labor force participation. The presence of a treatment group and a control group before and after the shock prompts one to employ a difference-in-difference approach to identify the causal impact of the shock on different outcomes. However, a key assumption for the DID approach is the *parallel trend* assumption, i.e., treated and control areas would follow a similar trend in the absence of the microcredit

[25] See Desai et al. (2010) for a detailed description on this survey.

ban. While we cannot test the parallel trend assumption directly, we can test one implication of the Parallel trend assumption – in the pre-shock period, time trends in the outcome are the same in treated and control units (i.e., parallel pre-trend). We test the validity of our identifying assumption, and find that the identification assumption is not satisfied for our main outcome variables.

To overcome this problem, we employ a Synthetic Difference-in-Differences strategy (SDID) proposed by Arkhangelsky et al. (2021). The method re-weights units and matches pre-treatment trends. It also allows for selection through unit-specific and time-specific fixed effects that are additive under the parallel trends assumption. Under this approach, we compare the outcomes of exposed districts (treated group) with that of a weighted combination of non-exposed districts (control group) which has similar pre-treatment trends as the treated group. We use the unit weights and time weights derived from SDID to re-weight our district panel data in the regressions. We use a R package developed by Arkhangelsky et al. (2021) to calculate the weights. For the ASER data, we match districts based on their numbers of households, numbers of mothers/fathers, numbers of mothers/fathers belong to the Scheduled Caste or Tribes, number of mothers/fathers who are literate, numbers of mothers/fathers who are ill and could not work, numbers of mothers/fathers who work, average number of household members, average mothers' age, average mothers' highest achieved education level, and share of mothers who have gone to schools. For the NSSO data, we match districts based on their share of households in the rural/urban area, share of male/female, average number of household members, average household annual income, share of never married women, share of married women, and share of household belong to the Scheduled Caste or Tribes.

For a district i in state j and year t, we then estimate the following regression specifications:

$$Y_{it} = \alpha_i + \alpha_t + \sum_{t=a}^{b} \beta_t \ Exposed_i \times 1(Year = t) + \varepsilon_{it} \tag{10}$$

$$Y_{it} = \alpha_i + \alpha_t + \beta \ Exposed_i \times Post_t + \varepsilon_{it} \tag{11}$$

where Y_{it} are a set of outcome variables of a district i in year t such as school enrollment and working conditions. $Exposed_i$ is a time-invariant definition that takes the value 1 if a district has micro-finance institutions and is in Andhra Pradesh. Equation 10 is a standard event-study design where $1(Year = t)$ takes the value 1 in year t and 0 otherwise. We take 2009, which is the year before the halt of micro-finance institutions' operation in Andhra Pradesh, as the omitted base year. a equals to 2007 in the ASER data and is 2004 in the NSSO data; b equals to 2013 in the ASER data and is 2012 in the NSSO data. In Equation

11, we pool the pre and post crisis years together and define a variable $Post_t$ that takes the value 1 for the years 2010-2013 in the ASER data (for the years 2010-2012 in the NSSO data) and 0 otherwise. α_i are district fixed effects that control for all observed and unobserved characteristics of a district that are time invariant; and α_t are year fixed effects. As we use a vector of district observables to construct the weights, we do not control them in our regression specification. Weights derived from SDID are used in equations 10 and 11. Standard errors are clustered at the state level for statistical inference.

For the IHDS data, we employ the following specification to estimate the impact of microcredit ban on child j:

$$Y_{jr} = \alpha_j + \alpha_r + \beta \ Exposed_j \times Post_r + \gamma X_{jr} + \epsilon_{jt} \tag{12}$$

where Y_{jt} are a set of outcome variables of a child j in survey round r such as school enrollment status, working status, and working hours. $Exposed_j$ is a time-invariant definition that takes the value 1 if a child is in a district that has micro-finance institutions and is in Andhra Pradesh. $Post_r$ takes the value 1 if it is the second round survey in 2011-12 and 0 if it is the first round survey in 2004-05. α_j are individual fixed effects that control all observed and unobserved characteristics of a child that are time invariant; and α_r are survey round fixed effects. X_{jr} is a vector of controls including a child's age, a child's father's and mother's education level and working condition, if the household belongs to urban or rural area, if the household owns or cultivates any land, if the household owns livestock, the household's total assets, annual total consumption, and annual total income.

6 Findings

6.1 Impact on Child Education

We begin by examining the impact of micro-finance ban on school enrollment of children aged between 4 and 16. We report the estimated coefficients $\hat{\beta}_t$ from the event-study specification (equation (10)) in Figure 1. By construction, there is no difference in school enrollment between districts in AP and the (synthetic control) districts in other states/UTs before the ban. The estimated coefficient in the pre periods are small and statistically insignificant.[26]

[26] We also display the event study graph on $\hat{\beta}_t$ in Appendix Figure C.2 not using the weights derived from synthetic difference-in-difference. As is shown, there are pre trends if not re-weighting our district panel data.

Yet, we see a substantial difference between the two groups after the 2010 ban, which is negative and persistent over the four years that follow. Districts in AP report 2.9-8.4 p.p. lower overall school enrollment compared to the control districts.

There is heterogeneity in the treatment effects. We display event study graphs by the level of schooling and age in Figure 2. Figures 2(a), 2(b), and 2(c) show a similar trend as in Figure 1 while Figure 2(d) presents an opposite post-period trend. Early levels of schooling such as primary, middle, and secondary school enrollment fall significantly after the shock. The treatment effect on higher secondary schooling, on the other hand, is positive and statistically significant. The results are consistent with our propositions in Section 3. Due to dynamic complementarities, the marginal return to education for children in the senior grades is much higher than for children in the junior grades. Households would thus let the younger children drop out of school to save money and allow the elder kids to stay at the school.

Table 1 reports the results from a standard difference-in-difference specification (equation (11)).[27] From columns (1) to (4), we observe reductions in the overall enrollment of children aged 4-16 (6.0 p.p.), in the primary school enrollment of children aged 4-10 (4.3 p.p.), in the middle school enrollment of children aged 11-13 (5.5 p.p.), and in the secondary school enrollment of children aged 14-16 (7.8 p.p.). Given the pre-ban average overall school enrollment rate of 80 percent, this effect size translates to a reduction of 7.5% in the overall school enrollment. In column (5), we see a 3.3 p.p. increase in the higher secondary school enrollment for children aged 14-16, which is equivalent to a 66% increase.

6.2 Impact on Child Labor

We then explore the effects of microcredit shock on the labor market participation of children aged between 4 and 17 using NSSO, Employement and Unemployment data. We examine various type of working conditions: self-employment activities, employed for wage/salary, either engaging in self-employment activities or being employed for wage/salary, domestic duties, and vocational training. Table 2 displays the results. The micro-finance ban led to a statistically significant decrease in children aged 4-17 participating in self-employment activities. Children from the policy-exposed areas are 33.3% (1 p.p.) less likely to participate

[27] We report the estimated coefficients $\hat{\beta}$ using NSSO data in Appendix Table C.2 and using IHDS data in Appendix Table C.3 panel A. The results in Appendix Table C.2 are similar to the results in Table 1. The pattern of $\hat{\beta}$'s in Appendix Table C.3 is also similar to Table 1 though $\hat{\beta}$ is positive for the secondary school enrollment. It can be due to the fact that we do not restrict data to a specific age group (i.e. $14 \sim 17$).

in household enterprises than children in the non-exposed districts. To the extent the microcredit ban tightens the liquidity constraints of the exposed households, affecting capital flows in the household enterprises, this result should not come as a surprise. The effect of the shock on the likelihood of a child working in wage-earning activities is not statistically significant. We, however, observe an increase in the likelihood that children participates in domestic chores in the treated areas post the policy change.

An investigation into the effect of the ban on children's labor force participation by age group reveals interesting results. As seen in panels B to D of Table 2, the reduction in the likelihood of employment in household enterprises are mainly driven be children from the age group of 14-17. The probability of working in household enterprises for children belonging to this age group is 3.2 p.p. lower. The corresponding effect for the younger age groups are negligible and not statistically significant. With regard to wage-earning activities, we observe a different picture. While we found no effect overall of the credit ban on children's wage earning activities (panel A of Table 2), we observe heterogeneity in the treatment effect. The likelihood of working for wage/salary increases significantly for younger children (panel B of Table 2) and decreases significantly for elder children (panel D of Table 2). Children aged 14-17 are also 62.5% (2.5 p.p., $p < 0.01$) less likely to go for vocational training. The results are in line with our propositions in Section 3 where younger kids drop out of school and work to subsidize families while adult children stay at schools.

7 Alternative Hypothesis: Strategic Allocation of Households Resources by Birth-Order and Gender of the Child

We explore the possibility if the findings are consistent with an alternative hypothesis: strategic investment decisions by households in children by birth-order and gender. Low birth order children are breast fed more (Jayachandran and Kuziemko, 2015) but receive less time from their mothers (Birdsall, 1979, Lindert, 1977) and resources from the family (Jayachandran and Pande, 2017; Behrman, 1988). Despite these endowment differences, the evidence on effect of birth order on education is mixed. Some studies find a positive effect (cite) while others a negative one.

In order to distinguish this channel from dynamic complementarities in education, we leverage and analyze education decisions in the cases of one-child and multi-child families. To

this end, we use the IHDS data. Since this is a two-year (2005 and 2012) panel data, we rely on the traditional Difference-in-Difference estimates, as opposed to Synthetic Difference-in-Difference estimates. As a first-pass, we show that the earlier results we found with regard to children's school enrollment and labor market participation, also holds in the IHDS data using the DID approach. As seen in panel A column (1) of Table 3, the effect of the micro-finance ban on school enrollment is significantly lower for the children in the treated districts. On the extensive margin, from columns (2) to (5) in panel A, we observe an overall reduction in labor participation which is driven by farming and animal care. Meanwhile, more children work for wage/salary in the treated districts than in the control districts. We observe similar pattern on the intensive margin (panel B Table 3). Although the total working hours decreased, children in the AP districts spent more time on wage/salary activities after the ban.

Once we establish that our main empirical findings also hold true in the IHDS data, we test our model's propositions empirically. We first look at the households with only one school-aged kids. In Table 4, we see that the negative effect of micro-finance ban on school enrollment is much larger for households with only one school-aged kid (-14.8% vs. -10.9%). Similarly, the effect of the shock on the likelihood of the children working for salary/wage is much higher for those households (5.9% vs. 1.6%). We then look at whether the treatment effect among these households vary by children's age. To this end, we define *older kid* dummy that takes a value if the child was aged greater than or equal to 7 years old in the 2005 survey (14 years old in 2012). We find that effect on school enrollment is higher, albeit imprecise, for the kids who are older compared to the ones who are younger amongst households with one child. However, the increase in work for wage/salary is driven by older children in households with one kid.

Next, we look at the households with multiple kids and explore the heterogeneity in the treatment effect by the birth order of a child in these families. We define *Younger Sibling* as a dummy variable that takes a value of one if the child has elder siblings. Results are reported in Table 5. Consistent with the prediction of our model, we find that the negative effect on school enrollment is driven by younger siblings. More precisely, school enrollment is 10 percentage points lower for the younger siblings than the elder siblings. We see a similar picture with regard to child labor: younger siblings are about 5 percentage point more likely to be engaged in any kinds of child labor compared to the elder kids.

Subsequent to establishing our results in this data, we look at sibling pairs in different age brackets and grade levels. We categorize households into four groups: households only having kids aged less than 4 in 2005 (so that the children are 11 or below in 2012) enrolled

in primary school grades, households only having kids aged between 4 and 7 in 2005 (8 and 14 in 2012) enrolled in middle school grades, households only having kids aged more than 7 in 2005 (older than 14 in 2012) enrolled in senior and senior secondary school grades, and households having one kid aged more than 7 (older than 12) and one kid aged less than 4 in 2005 (aged 9 or below in 2012). Table 6 displays the results on the four sub-samples with household fixed effects utilizing within household variation. Panel A shows that among siblings who are age 11 or below in 2012, such that they are in the primary school going age, it is the younger child who continues to be enrolled while the older child increases farm work. Very young children who cannot supply labor are not at the margin of contributing to the household income. Thus, for these children, we see the reversal of enrollment patterns by birth order. If investments by birth-order were driving our results, in that older children remained in school because of larger investments by parents in such children resulting in higher ability, we would continue to see older children remaining in school among this age group. However, do not observe that. In Panel B and C, when the children age such that both siblings can potentially contribute to the household income, we see patterns supporting our model. Children in higher grades remain in school, while those in lower grades increase labor supply. In comparing sibling aged 11 or below in 2012 with those 14 or above in Panel D (so that one has age appropriate for primary school and the other for senior school), this pattern continues to be exhibited. Younger sibling is less likely to enroll in school and more likely to work. Taken together these patterns which change with age of siblings cannot be rationalized consistently by a birth-order endowment differences explanation.

8 Conclusion

In this paper we explore the effect of income shocks on children's school attendance and labor market outcomes. We show that negative income shock in the form of a ban on micro-finance activities is associated with overall lower school enrollment and lower participation of children in self-employment activities. In addition, younger children or children in early years of schooling are affected most by the negative income shock. Such children tend to engage more in wage-earning activities. Our findings have very important insights for policy design. Policy programs designed to protect children from dropping out of school during economic hardship ought to be first targeted towards younger children of school going age especially if resources are scarce.

Shah and Steinberg (2017) find that positive income shocks resulting from higher rainfall decrease human capital and increase child labor between ages of 5 and 16, highlighting

that the opportunity cost of schooling is an important determinant of human capital. Our findings indicate that in presence of dynamic complementarities, the opportunity cost of schooling varies between primary-middle school aged and senior secondary aged children. Thus, the effect of opportunity cost of schooling on human capital is not homogeneous for all children.

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Tables

Table 1: Enrollment at the District Level by Age and Education Level (ASER)

	(1)	(2)	(3)	(4)	(5)
Ages	Overall (4~16)	Primary (4~10)	Middle (11~13)	Secondary (14~16)	Higher Secondary (14~16)
Exposed districts × Post MFI ban	-0.060***	-0.043***	-0.055***	-0.078***	0.033***
	(0.010)	(0.009)	(0.007)	(0.009)	(0.005)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pre-ban control mean	0.80	0.74	0.61	0.43	0.05
R^2	0.64	0.57	0.75	0.75	0.74
No. of Districts	206	206	206	206	206
N	1,427	1,427	1,427	1,427	1,427

Notes: "Enrolled" is a dummy variable equal to one if a child is enrolled at a primary school, middle school, secondary school, or higher secondary school currently. We collapsed the ASER data at the district level. Before collapsing the data, we kept observations belonging to a certain age group (e.g. age between 4 and 16, age between 4 to 10, age between 11 and 13, and age between 14 and 16). All regressions include district and year fixed effects. Standard errors are clustered at the state level. District weights from synthetic difference-in-difference method are applied. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 2: Working Conditions at the District Level by Age (NSSO)

	(1)	(2)	(3)	(4)	(5)
		Work		Vocational	Domestic
	Any	Self-Employment	Wage/Salary	Training	Duties
Panel A. All children (4~17)					
Exposed districts x Post MFI ban	-0.004	-0.010***	0.008	-0.006***	0.005**
	(0.008)	(0.002)	(0.008)	(0.001)	(0.002)
Pre-ban Control Mean	0.14	0.03	0.11	0.04	0.04
R^2	0.64	0.45	0.61	0.49	0.41
Panel B. Age between 4 and 10					
Exposed districts x Post MFI ban	0.022*	-0.001	0.026*		-0.001
	(0.010)	(0.001)	(0.013)		(0.001)
Pre-ban Control Mean	0.13	0.00	0.13		0.01
R^2	0.59	0.26	0.59		0.21
Panel C. Age between 11 and 13					
Exposed districts x Post MFI ban	-0.010	-0.005	0.001		0.010**
	(0.007)	(0.003)	(0.006)		(0.004)
Pre-ban Control Mean	0.08	0.02	0.06		0.04
R^2	0.46	0.44	0.37		0.30
Panel D. Age between 14 and 17					
Exposed districts x Post MFI ban	-0.061***	-0.032***	-0.030***	-0.025***	0.017***
	(0.007)	(0.003)	(0.005)	(0.008)	(0.004)
Pre-ban Control Mean	0.19	0.09	0.10	0.04	0.12
R^2	0.66	0.39	0.53	0.47	0.38
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
No. of Districts	201	201	201	201	201
N	1,809	1,809	1,809	1,809	1,809

*Notes:*Any = Participate in self-employment activities or work for wage/salary. Self-Employment = Work in the household enterprise (self-employment). Wage/Salary = Work at non-household enterprises. Vocational Training = An individual receive any forms of vocational training including formal vocational training, non-formal vocational training, self-learning, learning on the job, and others. Domestic Duties = Engage in domestic duties only. We collapsed the NSSO data at the district level. In panel A, before collapsing the data, we kept observations aged between 4 and 17. In panels B to D, before collapsing the data, we kept observations belonging to a certain age group (i.e. age between 4 to 10, age between 11 and 13, and age between 14 and 17). All regressions include district and year fixed effects. Standard errors are clustered at the state level. District weights from synthetic difference-in-difference method are applied. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3: Enrollment & Employment (IHDS): Individual Level

	(1)	(2)	(3)	(4)	(5)
Panel A. Overall Enrollment & Employment					
	School	Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Exposed districts × Post MFI ban	-0.109***	-0.082***	-0.095***	-0.000	0.016*
	(0.023)	(0.026)	(0.026)	(0.003)	(0.008)
p-value	[0.000]	[0.002]	[0.000]	[0.923]	[0.052]
Sharpened q-value	[0.001]	[0.003]	[0.001]	[0.227]	[0.027]
Pre-ban Control Mean	0.50	0.02	0.02	0.00	0.00
R^2	0.58	0.60	0.59	0.50	0.52
Panel B. Working Hours					
		Ln(Work Hours)	Ln(Farm Hours)	Ln(Business Hours)	Ln(Wage/Salary Hours)
Exposed districts × Post MFI ban		-0.290***	-0.374***	-0.000	0.106*
		(0.105)	(0.094)	(0.015)	(0.062)
p-value		[0.006]	[0.000]	[0.988]	[0.089]
Sharpened q-value		[0.010]	[0.001]	[0.329]	[0.064]
Pre-ban Control Mean		0.04	0.03	0.00	0.00
R^2		0.57	0.57	0.50	0.52
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	20,826	20,826	20,826	20,826	20,826

Notes: "School Enrollment" is a dummy variable equal to one if a child is enrolled at a school currently. "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Work Hours" include hours of working in farm, business, and wage/salary work. We restrict our sample to kids who are less than or equal to 11 years old in the 2005 survey. All regressions include individual and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01. We also display p-value and sharpened q-value (Anderson, 2008) in the brackets.

Table 4: Employment (IHDS): Households with *One* School-Aged Kid

	(1) School	(2)	(3)	(4)	(5)
		Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Panel A. All one school-aged kids in the household					
Exposed districts × Post MFI ban	-0.148**	-0.028	-0.058*	0.001	0.059***
	(0.066)	(0.039)	(0.034)	(0.011)	(0.013)
Pre-ban Control Mean	0.51	0.02	0.02	0.00	0.00
R^2	0.54	0.63	0.61	0.60	0.57
Panel B. Younger vs. Older Kid					
Exposed districts × Post MFI ban	-0.143*	-0.032	-0.028	-0.000	0.014
	(0.080)	(0.036)	(0.033)	(0.011)	(0.014)
Exposed districts × Post MFI ban × Older kid	0.123	-0.023	-0.077	-0.001	0.075**
	(0.114)	(0.059)	(0.071)	(0.014)	(0.035)
Pre-ban Control Mean of Younger Kid	0.18	0.01	0.01	0.00	0.00
R^2	0.79	0.65	0.63	0.60	0.60
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	4,452	4,452	4,452	4,452	4,452

Notes: "School Enrollment" is a dummy variable equal to one if a child is enrolled at a school currently. "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Older kids" is a dummy variable equal to one if the child was aged greater than or equal to 7 years old in the 2005 survey. We restrict our sample to kids who are less than or equal to 11 years old and are the only school-aged kid in a household in the 2005 survey. All regressions include household and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 5: Employment (IHDS): Households with *Multiple* School-Aged Children

	(1) School	(2)	(3)	(4)	(5)
		Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Exposed districts × Post MFI ban	-0.032	-0.167***	-0.155***	-0.024**	-0.016
	(0.032)	(0.030)	(0.030)	(0.009)	(0.021)
Exposed districts × Post MFI ban × Younger Sibling	-0.106**	0.047*	0.037**	0.010	0.013
	(0.050)	(0.025)	(0.017)	(0.007)	(0.022)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pre-ban Control Mean of Elder Sibling	0.72	0.04	0.04	0.00	0.00
R^2	0.47	0.46	0.45	0.32	0.32
N	17,685	17,685	17,685	17,685	17,685

Notes: "School Enrollment" is a dummy variable equal to one if a child is enrolled at a school currently. "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Younger Sibling" is a dummy variable equal to one if the child has elder siblings who aged less than or equal to 11 years old in the 2005 survey. We restrict our sample to kids who are less than or equal to 11 years old and have siblings aged less than or equal to 11 years old in the 2005 survey. All regressions include household and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 6: Employment (IHDS): Households with *Multiple* School-Aged Children (By Education Level)

	(1)	(2)	(3)	(4)	(5)
	School	Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Panel A. All kids' age < 4 in 2005-06 (Primary School)					
Exposed districts × Post MFI ban	-0.070	-0.080**	-0.098***	0.014	
	(0.063)	(0.035)	(0.030)	(0.019)	
Exposed districts × Post MFI ban × Younger Sibling	0.122*	0.013	0.029	-0.012	
	(0.062)	(0.026)	(0.019)	(0.018)	
Pre-ban Control Mean	0.07	0.01	0.01	0.00	
R^2	0.92	0.49	0.49	0.39	
N	1,301	1,304	1,304	1,304	
Panel B. All kids' age $\in [4,7]$ *in 2005-06 (Middle School)*					
Exposed districts × Post MFI ban	0.117**	-0.267***	-0.245***	-0.010	-0.023
	(0.057)	(0.060)	(0.048)	(0.020)	(0.037)
Exposed districts × Post MFI ban × Younger Sibling	-0.359***	0.120**	0.121***	0.000	-0.021
	(0.078)	(0.048)	(0.046)	(0.014)	(0.034)
Pre-ban Control Mean	0.82	0.01	0.01	0.00	0.00
R^2	0.51	0.52	0.52	0.38	0.37
N	1,335	1,337	1,337	1,337	1,337
Panel C. All kids' age > 7 in 2005-06 (Secondary and Higher Secondary School)					
Exposed districts × Post MFI ban	0.119*	-0.272***	-0.141**	-0.065***	-0.030
	(0.062)	(0.082)	(0.065)	(0.022)	(0.082)
Exposed districts × Post MFI ban × Younger Sibling	-0.173**	0.172*	0.109	0.015	-0.044
	(0.073)	(0.096)	(0.074)	(0.027)	(0.083)
Pre-ban Control Mean	0.92	0.06	0.05	0.00	0.01
R^2	0.60	0.60	0.56	0.38	0.49
N	1,071	1,071	1,071	1,071	1,071
Panel D. One kid's age <4 *and One kid's age* >7 *in 2005-06*					
Exposed districts × Post MFI ban	0.103	-0.388***	-0.282***	-0.027**	-0.188***
	(0.097)	(0.069)	(0.062)	(0.013)	(0.039)
Exposed districts × Post MFI ban × Younger Sibling	-0.119	0.164***	0.085**	0.019*	0.165***
	(0.112)	(0.039)	(0.035)	(0.011)	(0.032)
Pre-ban Control Mean	0.89	0.06	0.05	0.01	0.00
R^2	0.62	0.50	0.47	0.26	0.36
N	1,524	1,524	1,524	1,524	1,524
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: "School Enrollment" is a dummy variable equal to one if a child is enrolled at a school currently. "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Younger Sibling" is a dummy variable equal to one if the child has elder siblings who aged less than or equal to 11 years old in the 2005 survey. We restrict our sample to kids who are less than or equal to 11 years old and have siblings aged less than or equal to 11 years old in the 2005 survey. All regressions include household and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Figures

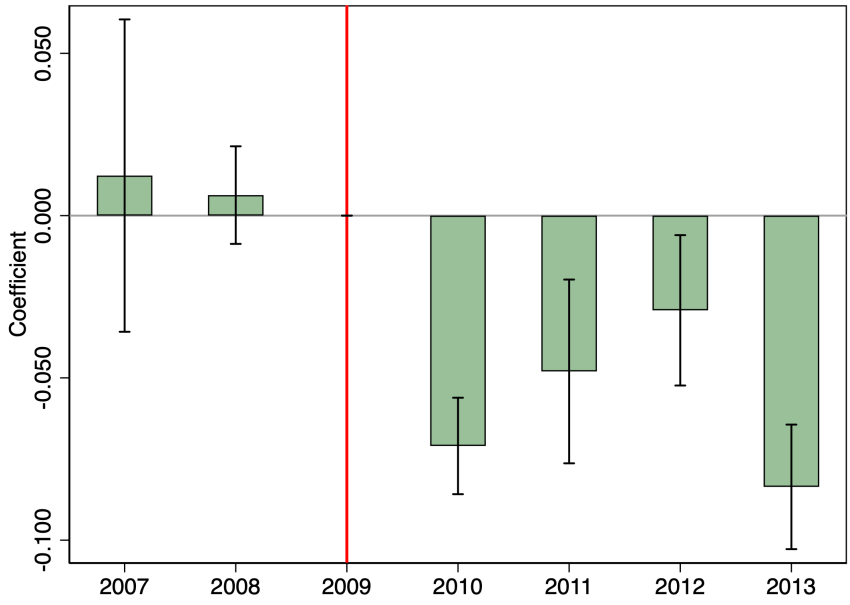
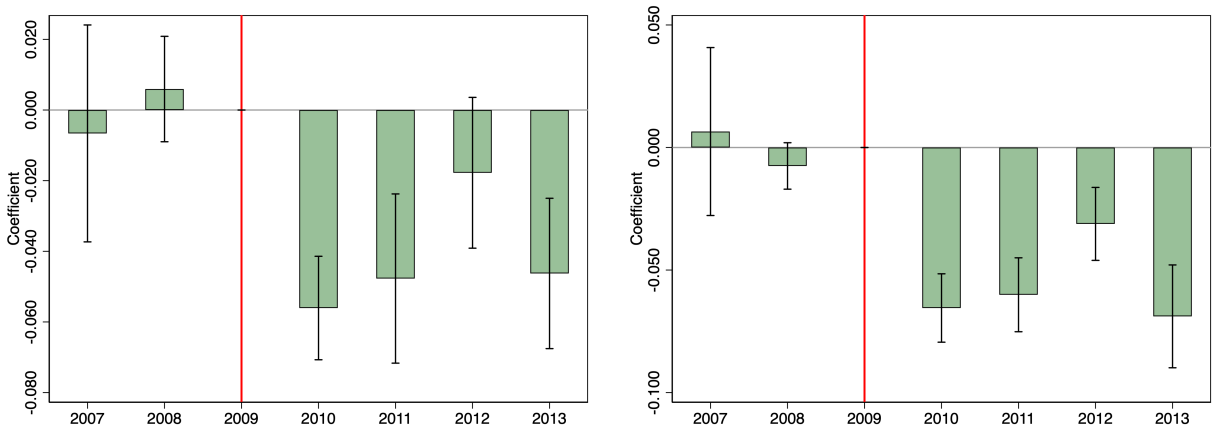


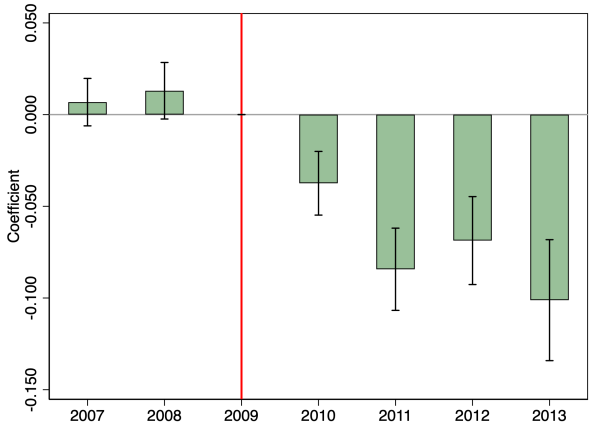
Figure 1: Event Study Graph: Enrollment at District Level (ASER)

Notes: "Enrolled" is a dummy variable equal to one if a child is enrolled at a primary school, middle school, secondary school, or higher secondary school currently. We collapsed the ASER data at the district level. Before collapsing the data, we kept observations aged between 4 and 16. The regression includes district and year fixed effects. Standard errors are clustered at the state level. District weights from synthetic DID are applied. Confidence intervals are at the 95 percent level.

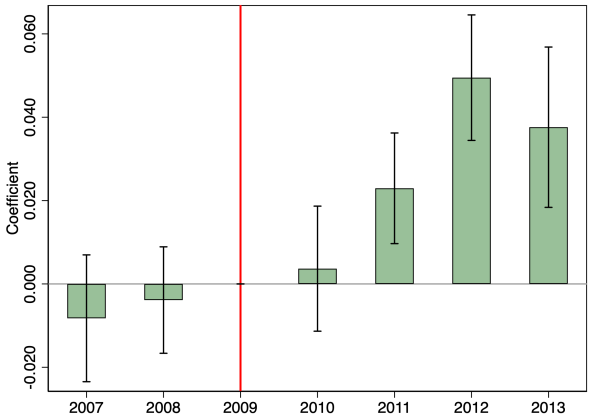


(a) Primary Schools (Age 4~10)

(b) Middle Schools (Age 11~13)



(c) Secondary Schools (Age 14~16)



(d) Higher Secondary Schools (Age 14~16)

Figure 2: Event Study Graphs: Enrollment at District Level by Age Groups (ASER)

Notes: We restricted the ASER data for observations aged between 4 and 10, 11 and 13, and 14 and 16, and then we collapsed the ASER data at the district level. All regressions include district and year fixed effects. Standard errors are clustered at the state level. District weights from synthetic DID are applied. Confidence intervals are at the 95 percent level.

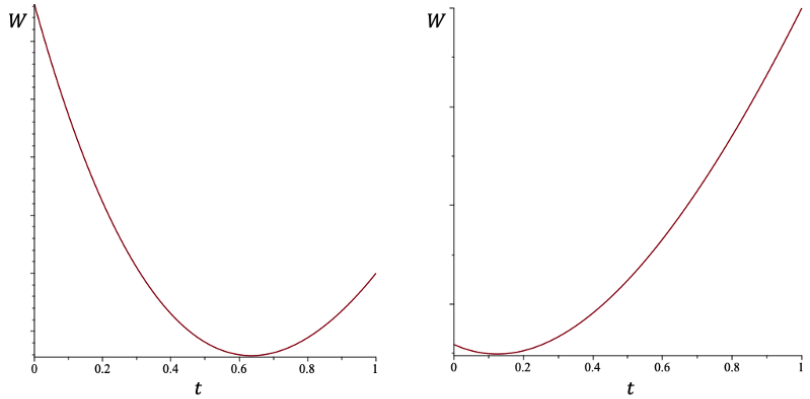
Appendices

A Mathematics of the Theoretical Framework

In the canonical model where the parent has one child, a household can maximize one's utility when the lifetime income constraint reaches the maximum value. A household's lifetime income constraint is

$$W = w_p + w_c t - v(1-t) + \frac{w_p}{1+r} + \frac{w_c}{1+r}\gamma \exp(g(1-t)). \tag{13}$$

We display W in Appendix Figure A.1. As is shown, W is U-shaped for $t \in [0,1]$, which suggests that W is either maximized at $t=0$ or $t=1$. We will have W maximized at $t=0$ when $W(t=0) \geq W(t=1)$ which is equivalent to $r \leq \frac{\gamma w_c(\exp(g)-1)}{w_c+v} - 1$. Thus, if the interest rate is low, the parent will let the child go to school to maximize household's lifetime income.



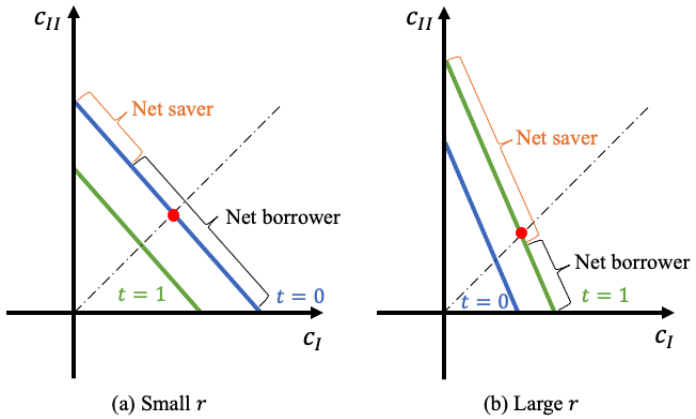
(a) Small r (b) Large r

Figure A.1: One-Child: Lifetime Income Constraint & Child's Working Time

Notes: We plot how the lifetime income constraint, W, changes with the child's extent of work. In Figure A.1(a), we assume that r is small; in Figure A.1(b), we assume that r is large.

In Appendix Figure A.2, we display the household's lifetime budget constraint under two conditions, small r and large r. Since $\beta(1+r)=1$, the household optimal choice is $\{c_I^* = c_{II}^*, t^* = 0, b^* > 0\}$ if the interest rate is not too high. When the interest rate is high enough, the household will not send the child to school and will become a net saver.

After the government bans MFIs from issuing loans, households can no longer borrow money from them. We abstract away from other sources of credit and set a borrowing constraint on households where $A=0$. The best a household who is a net borrower in a well-functioning



(a) Small r (b) Large r

Figure A.2: Lifetime Budget Constraint

Notes: In Figure A.2(a), we assume that r is small and plot two cases of lifetime budget constraint where $t = 0$ and $t = 1$; in Figure A.2(b), we assume that r is large. The larger the r is, the more likely the household is a net saver. The red points are the optimal level of consumption. The blue lines are the lifetime budget constraints when $t = 0$; and the green lines are when $t = 1$.

credit market can do is:

$$c_I = w_p + w_c t - v(1-t), \tag{14}$$

$$c_{II} = w_p + w_c \gamma \exp(g(1-t)), \tag{15}$$

$$\text{and } b = 0. \tag{16}$$

Thus, these households can only consume as much as they earn in each period. A household then solves for t to maximize equation (5). The derivative of U with respect to t is

$$\frac{\partial U}{\partial t} = \frac{w_p \left(w_c + v - \beta w_c \gamma g \exp(g - gt)\right) + w_c \gamma \exp(g - gt)\left(w_c + v - \beta g (w_c t - v(1-t))\right)}{\left(w_p + w_c t - v(1-t)\right)\left(w_p + w_c \gamma \exp(g(1-t))\right)} \tag{17}$$

whose sign is determined by the numerator and the numerator can be re-written as equation (6). If $g > \frac{w_c+v}{w_p-v}\left(\frac{w_p}{\beta w_c \gamma e^g} + \frac{1}{\beta}\right)$, then U is maximized at $t^B = 0$; if $g < \frac{w_c+v}{w_p+w_c}\left(\frac{w_p}{\beta w_c \gamma} + \frac{1}{\beta}\right)$, then U is maximized at $t^B = 1$; if $g \in \left[\frac{w_c+v}{w_p+w_c}\left(\frac{w_p}{\beta w_c \gamma} + \frac{1}{\beta}\right), \frac{w_c+v}{w_p-v}\left(\frac{w_p}{\beta w_c \gamma e^g} + \frac{1}{\beta}\right)\right]$, then U is either maximized at $t^B = 1$ or $t^B \in (0,1)$. Here, we discuss the third case where an interior solution to t might exists.

Proof of Proposition 3. From $h = \gamma \exp(g(1-t))$, we know that a child's human capital depends both on the time spent on schooling and the grade. So, for a given level of h, a child will substitute away from spending more time on schooling as one's grade goes up. That is, t increases with g.

The Lagrangian in the case of $A = 0$ is

$$\mathscr{L} = \ln c_I + \beta \ln c_{II} - \lambda_1[c_I + v - vt - w_p - w_c t] - \lambda_2[c_{II} - w_p - w_c \gamma \exp(g(1-t))], \tag{18}$$

where λ_1 and λ_2 are multipliers. Assuming that there is an interior solution, then the first-order conditions give:

$$\frac{c_{II}}{\beta c_I}(v + w_c) = w_c \gamma g \exp(g(1-t)). \tag{19}$$

Combining the above equation and the two period budget constraints yields

$$\begin{aligned}
&\frac{w_p + w_c \gamma \exp(g(1-t))}{\beta\left(w_p + w_c t - v(1-t)\right)}(v + w_c) = w_c \gamma g \exp(g(1-t)), \\
&w_p(w_c + v) + w_c \gamma e^{g-gt}(w_c + v) = \beta(w_p - v) w_c \gamma g e^{g-gt} + \beta(w_c + v) w_c \gamma g t e^{g-gt}.
\end{aligned} \tag{20}$$

Differentiating both sides of equation (20) implicitly with respect to g yields

$$\begin{aligned}
\frac{Left}{w_c \gamma} =& (w_c + v)e^{g-gt} - t(w_c + v)e^{g-gt} - (w_c + v)e^{g-gt} g \frac{dt}{dg}, \\
\frac{Right}{w_c \gamma} =& \beta g t(w_c + v)(1-t) + \beta e^{g-gt}\left((1 + g - gt)(w_p - v) + (g + t)(w_c + v)\right) \\
& - \frac{dt}{dg}\left(\beta g^2 (w_p - v)e^{g-gt} + \beta g^2 t(w_c + v)\right), \\
Left =& Right \Longrightarrow \\
& \frac{dt}{dg}\left\{\beta g^2 (w_p - v)e^{g-gt} + \beta g^2 t(w_c + v) - (w_c + v) g e^{g-gt}\right\} = \\
& \beta g t(w_c + v)(1-t) + \beta e^{g-gt}(1 + g - gt)(w_p - v) + e^{g-gt}(w_c + v)(\beta g - 1 + \beta t - t), \\
\frac{dt}{dg} =& \frac{\overbrace{\beta g t(w_c + v)(1-t) + \beta e^{g-gt}(1 + g - gt)(w_p - v)}^{>0} + e^{g-gt}(w_c + v)\overbrace{(\beta g - 1 + \beta t - t)}^{undetermined}}{\underbrace{\beta g^2 t(w_c + v)}_{\geq 0} + g e^{g-gt}\underbrace{[\beta g(w_p - v) - (w_c + v)]}_{undetermined}}.
\end{aligned}$$

We then evaluate $\frac{dt}{dg}$ at $t = 0$ since the optimal choice of t in a credit market without bans is 0.

$$\begin{aligned}
\frac{dt}{dg}\Big|_{t=0} &= \frac{\beta e^g (1+g)(w_p - v) + e^g (w_c + v)(\beta g - 1)}{g e^g [\beta g(w_p - v) - (w_c + v)]}, \\
&= \frac{\beta w_p - w_c + \beta g(w_p + w_c) - v(1+\beta)}{g[\beta g(w_p - v) - (w_c + v)]}.
\end{aligned} \tag{21}$$

The numerator in equation (21) is positive if $g > \frac{1}{\beta}\frac{w_c+v-\beta(w_p-v)}{w_p+w_c}$; the denominator is positive if $g > \frac{1}{\beta}\frac{w_c+v}{w_p-v}$. Suppose that $w_c + v - \beta(w_p - v) < 0$,[1] then we have:

- For $g \in \left(\frac{1}{\beta}\frac{w_c+v}{w_p-v}, \frac{w_c+v}{w_p-v}\left(\frac{w_p}{\beta w_c \gamma e^g} + \frac{1}{\beta}\right)\right]$, we have $\frac{dt}{dg}\big|_{t=0} > 0$. As g increases, a child will spend more time on work.
- For $g \in \left[\frac{w_c+v}{w_p+w_c}\left(\frac{w_p}{\beta w_c \gamma} + \frac{1}{\beta}\right), \frac{1}{\beta}\frac{w_c+v}{w_p-v}\right)$, we have $\frac{dt}{dg}\big|_{t=0} < 0$. Since t cannot be negative, we do not consider this case.

Therefore, when a child's grade g is within a certain range, the higher the grade the child is in, the more the parent will make him/her work to support the family. ■

In the extended model of two-child, a household's period budget constraints become:

$$c_I + e_1 + e_2 \le w_p + b + w_c t_1 + w_c t_2 \text{ in period I,} \tag{22}$$

$$c_{II} + (1+r)b \le w_p + w_c h_1 + w_c h_2 \text{ in period II.} \tag{23}$$

The lifetime income constraint for the household is

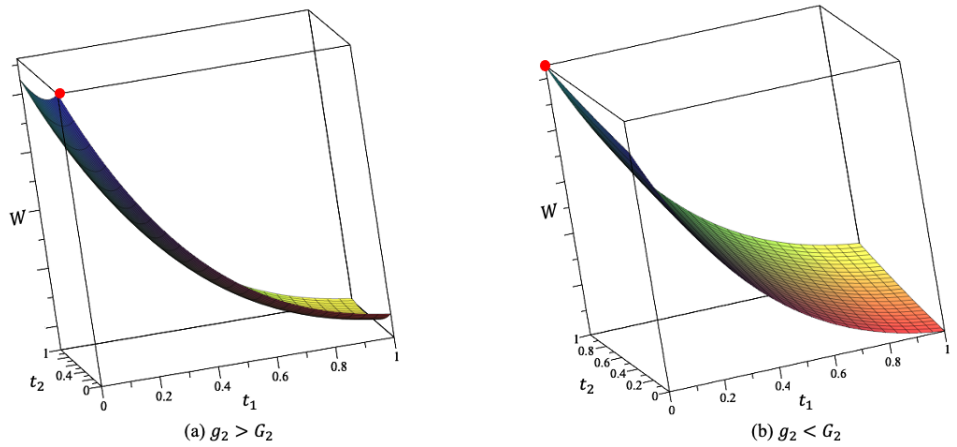
$$W = w_p + w_c t_1 + w_c t_2 - v(2 - t_1 - t_2) + \frac{w_p}{1+r} + \frac{w_c \gamma [\exp(g_1(1-t_1)) + \exp(g_2(1-t_2))]}{1+r} \tag{24}$$

We plot W in Appendix Figure A.3. It should be noticed that parents will only have incentives to send a child to school if $g_2 \ge G_2 = \ln\left(\frac{(1+r)(v+w_c)}{w_c\gamma} + 1\right)$. That is, the younger child will be more likely to be sent to school when the technology constant γ is large or the child has higher ability (i.e. small v). When parents can borrow freely, they will send both children to schools, $(t_1^*, t_2^*) = (0,0)$ if $g_2 \ge G_2$. If $g_2 < G_2$, then the parent will only keep the elder child at school, $(t_1^*, t_2^*) = (0,1)$. Hereafter, we assume that $g_2 \ge G_2$.

After the implementation of the MFI ban, the household's utility function can be re-written as:

$$U = \ln\left(w_p + w_c(t_1+t_2) - v(2 - t_1 - t_2)\right) + \beta \ln\left(w_p + w_c \gamma \left[e^{g_1(1-t_1)} + e^{g_2(1-t_2)}\right]\right); \tag{25}$$

[1] In the setup, we assume that $w_p \gg w_c \ge 1 > v > 0$.



(a) $g_2 > G_2$ (b) $g_2 < G_2$

Figure A.3: Two-Child: Lifetime Income Constraint & Child's Working Time

Notes: We plot how the lifetime income constraint changes with the children's extent of work. In both graphs, we assume that the interest rate is not too large. We have $G_2 = \frac{(1+r)(v+w_c)}{w_c\gamma} + 1$. The red point is where the lifetime income constraint is the largest. If $g_2 > G_2$, then the lifetime income constraint is largest at $(t_1, t_2) = (0,0)$; and if $g_2 < G_2$, then the lifetime income constraint is largest at $(t_1, t_2) = (0,1)$.

and its derivative with respect to t_i is

$$\frac{\partial U}{\partial t_i} = \frac{w_p\left(w_c + v - \beta w_c \gamma g_i e^{g_i - g_i t_i}\right)}{\left(w_p + w_c(t_1+t_2) - v(2-t_1-t_2)\right)\left(w_p + w_c\gamma\left[e^{g_1(1-t_1)} + e^{g_2(1-t_2)}\right]\right)} + \frac{w_c\gamma e^{g_i - g_i t_i}\left(w_c + v - \beta g_i(w_c t_i - v(1-t_i)\right)}{\left(w_p + w_c(t_1+t_2) - v(2-t_1-t_2)\right)\left(w_p + w_c\gamma\left[e^{g_1(1-t_1)} + e^{g_2(1-t_2)}\right]\right)} + \frac{w_c\gamma\left(e^{g_{-i} - g_{-i}t_{-i}}(w_c + v) - \beta g_i e^{g_i - g_i t_i}(w_c t_{-i} - v(1-t_{-i}))\right)}{\left(w_p + w_c(t_1+t_2) - v(2-t_1-t_2)\right)\left(w_p + w_c\gamma\left[e^{g_1(1-t_1)} + e^{g_2(1-t_2)}\right]\right)}, \tag{26}$$

where the sign of the derivative depends on the numerator. Similar to the one-child model, the parent's decision on child labor and schooling depends on the marginal return to education and the return to child labor, which we have discussed in section 3.3.

B Heterogeneity

We also explore the heterogeneity in the treatment effect gender, by household wealth status (i.e. below or above the poverty line), and by caste. Regression results are shown in Table B.1, B.2, and B.3 respectively. First, we do not spot gender differential effects on school enrollment or child labor. Second, children in poor families spend less time on farming or animal care as those families also lack these kinds of resources. Third, children who are from the low caste are in a disadvantaged place of work and thus have fewer opportunities to work and subsidize families.

Table B.1: Employment (IHDS): Above vs. Below Poverty Line

	(1)	(2)	(3)	(4)	(5)
	School	Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Exposed districts × Post MFI ban	-0.118***	-0.057**	-0.075***	-0.000	0.026***
	(0.025)	(0.027)	(0.026)	(0.003)	(0.008)
Exposed districts × Post MFI ban × Below Poverty Line	0.049	-0.034	-0.046*	0.005	0.010
	(0.065)	(0.054)	(0.028)	(0.008)	(0.052)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pre-ban Control Mean	0.52	0.02	0.02	0.00	0.00
R2	0.58	0.60	0.59	0.50	0.52
N	20,826	20,826	20,826	20,826	20,826

Notes: "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Work Hours" include hours of working in farm, business, and wage/salary work. We restrict our sample to kids who are less than or equal to 11 years old in the 2005 survey. "Below Poverty Line" is a dummy variable equal to one if the family was below the poverty line using 2005 definition. All regressions include individual and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B.2: Employment (IHDS): Boys vs. Girls

	(1)	(2)	(3)	(4)	(5)
	School	Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Exposed districts × Post MFI ban	-0.096***	-0.082***	-0.097***	0.001	0.015
	(0.030)	(0.025)	(0.025)	(0.004)	(0.011)
Exposed districts × Post MFI ban × Female	-0.027	0.001	0.004	-0.003	0.002
	(0.046)	(0.031)	(0.025)	(0.004)	(0.012)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pre-ban Control Mean	0.50	0.02	0.02	0.00	0.00
R2	0.58	0.60	0.59	0.50	0.52
N	20,826	20,826	20,826	20,826	20,826

Notes: "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Work Hours" include hours of working in farm, business, and wage/salary work. We restrict our sample to kids who are less than or equal to 11 years old in the 2005 survey. All regressions include individual and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B.3: Employment (IHDS): Low Caste vs. Others

	(1)	(2)	(3)	(4)	(5)
	School	Work			
	Enrollment	Any	Farm/Animal	Business	Wage/Salary
Exposed districts × Post MFI ban	-0.108***	-0.057**	-0.071***	-0.000	0.021**
	(0.027)	(0.026)	(0.026)	(0.003)	(0.009)
Exposed districts × Post MFI ban × Low Caste	0.002	-0.111**	-0.108**	0.000	-0.023*
	(0.064)	(0.047)	(0.045)	(0.005)	(0.013)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pre-ban Control Mean	0.50	0.02	0.02	0.00	0.00
R^2	0.58	0.60	0.59	0.50	0.52
N	20,826	20,826	20,826	20,826	20,826

Notes: "Any" is a dummy variable equal to one if a child is doing farm/animal care work, business work, or wage/salary work. "Work Hours" include hours of working in farm, business, and wage/salary work. "Low Caste" is a dummy variable if a child belongs to the Scheduled Castes (SCs) and Scheduled Tribes (STs), which are officially designated groups of people and among the most disadvantaged socioeconomic groups in India. We restrict our sample to kids who are less than or equal to 11 years old in the 2005 survey. All regressions include individual and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Additional Tables

Table C.1: District Statistics (2011 Census of India)

Variable	(1) Mean/SD	(2) Mean/SD	(3) (1)-(2)
Panel A. No MFIs Districts vs. Have MFIs Districts			
	No MFIs Districts (123)	Have MFI Districts (208)	t-test Difference
Ln(Population)	13.681	14.503	-0.822***
	(0.962)	(0.673)	(0.090)
Ln(Households)	12.044	12.927	-0.883***
	(0.942)	(0.686)	(0.090)
Sex ratio	1.065	1.044	0.021***
	(0.057)	(0.044)	(0.006)
Literacy rate	0.589	0.594	-0.004
	(0.104)	(0.095)	(0.011)
Literacy rate (Female)	0.513	0.516	-0.003
	(0.123)	(0.109)	(0.013)
Working Pop./Total Pop.	0.421	0.415	0.006
	(0.072)	(0.067)	(0.008)
Panel B. Have MFIs Districts: Districts in Other States vs. Districts in Andhra Pradesh			
	Other States (189)	Andhra Pradesh (19)	t-test Difference
Ln(Population)	14.447	15.061	-0.614***
	(0.677)	(0.243)	(0.157)
Ln(Households)	12.854	13.657	-0.804***
	(0.673)	(0.255)	(0.156)
Sex ratio	1.048	1.004	0.044***
	(0.044)	(0.018)	(0.010)
Literacy rate	0.595	0.575	0.020
	(0.099)	(0.046)	(0.023)
Literacy rate (Female)	0.518	0.499	0.019
	(0.113)	(0.058)	(0.026)
Working Pop./Total Pop.	0.409	0.479	-0.070***
	(0.067)	(0.030)	(0.015)

Notes: Data is from 2011 Census of India. Ln(Population) = Log of total population. Ln(Households) = Log of total number of households in the district. Working Pop./Total Pop. = Working population as a share of total population. In panel A, we compare districts that had MFIs to districts that did not have MFIs in 2008; in panel B, we compare districts that had MFIs and were in Andhra Pradesh to districts that had MFIs and were in other states. We conduct two-sample t test with equal variances in column (3). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Enrollment at the District Level by Age and by Education Level (NSSO)

	(1)	(2)	(3)	(4)	(5)
Education Level	Overall	Primary	Middle	Secondary	Higher Secondary
Ages	(4~17)	(4~10)	(11~13)	(14~17)	(14~17)
Exposed districts × Post MFI ban	-0.009	-0.011*	-0.044***	-0.063***	0.024**
	(0.011)	(0.005)	(0.010)	(0.018)	(0.011)
Pre-ban control mean	0.58	0.43	0.39	0.32	0.12
R^2	0.82	0.89	0.56	0.59	0.69
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N of Districts	201	201	201	201	201
N	1,809	1,809	1,809	1,809	1,809

Notes: We collapsed the NSSO data at the district level. Before collapsing the data, we kept observations belonging to a certain age group (e.g. age between 4 to 17, age between 4 to 10, age between 11 and 13, and age between 14 and 17). All regressions include district and year fixed effects. Standard errors are clustered at the state level. District weights from synthetic difference-in-difference method are applied. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C.3: Enrollment & Highest Completed Education (IHDS)

	(1) Enrolled Now	(2) Primary	(3) Middle	(4) Secondary	(5) Higher Sec.
Panel A. All Children					
Exposed districts × Post MFI ban	-0.089***	-0.128***	-0.015	0.082***	0.042***
	(0.021)	(0.033)	(0.026)	(0.015)	(0.016)
Pre-ban Control Mean	0.51	0.38	0.01	0.00	0.00
R^2	0.55	0.27	0.60	0.53	0.51
Panel B. Boys vs Girls					
Exposed districts × Post MFI ban	-0.066**	-0.105**	-0.022	0.073***	0.041***
	(0.030)	(0.052)	(0.026)	(0.020)	(0.012)
Post MFI ban × Female	0.044***	0.028	-0.005	-0.010*	0.001
	(0.016)	(0.019)	(0.011)	(0.006)	(0.004)
Exposed districts × Post MFI ban × Female	-0.049	-0.048	0.014	0.018	0.002
	(0.046)	(0.102)	(0.055)	(0.040)	(0.019)
Pre-ban Control Mean of Boys	0.52	0.38	0.01	0.00	0.00
R^2	0.55	0.27	0.60	0.53	0.51
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	21,916	21,916	21,916	21,916	21,916

Notes: We restrict our sample to kids who are less than or equal to 11 years old in the 2005 survey. All regressions include individual and year fixed effects. We also control for a kid's sex, age, rural or urban, if a household owned or cultivated land, if a household owned livestock, a household's total assets, if father/mother is literate, if father/mother has attended school, father's/mother's completed years of education, if father/mother is working, if father/mother has any major morbidity such as heart disease, cancer, and diabetes. Standard errors are clustered at the district level. * p < 0.1, ** p < 0.05, *** p < 0.01.

D Additional Figures

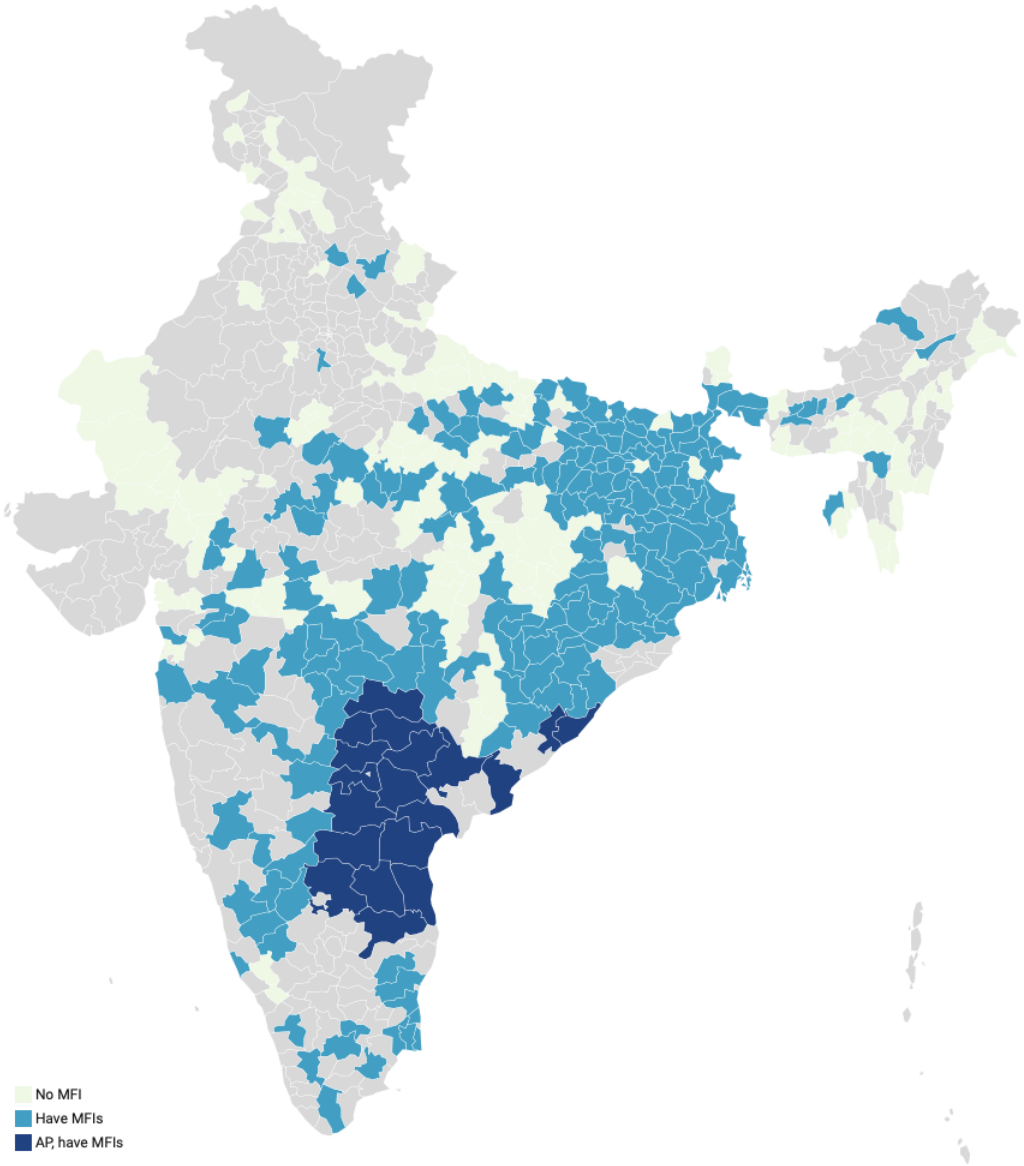


Figure C.1: Distribution of MFIs across Districts (2008)

Notes: We plot the distribution of microfinance institutions (MFIs) across districts in the map. We collected data from *The Bharat Microfinance Report: Quick Data 2008*. Gray area: we do not have information on these districts. Light green area: these districts did not have MFIs in 2008. Blue area: these districts had MFIs in 2008. Dark blue area: these districts were in the state of Andhra Pradesh and had MFIs in 2008.

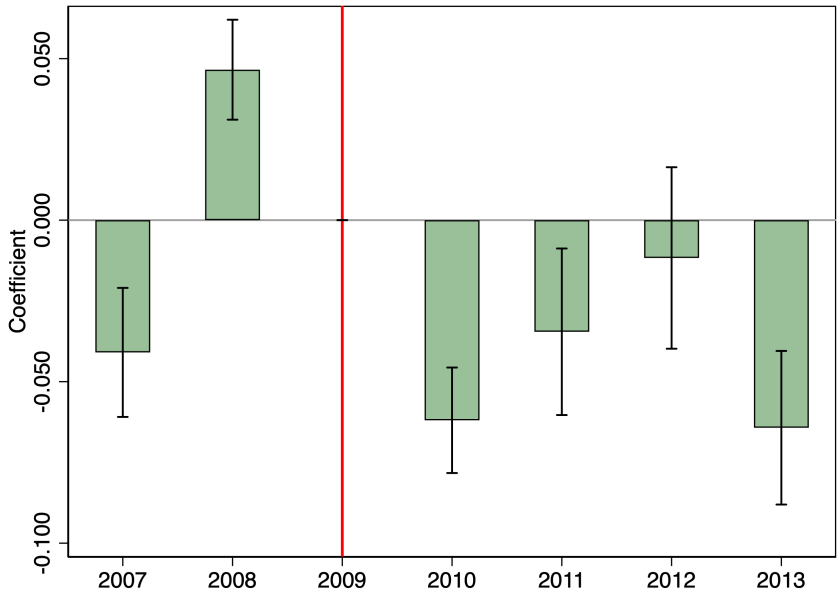


Figure C.2: Event Study Graph (Not Weighted): Enrollment at District Level (ASER)

Notes: "Enrolled" is a dummy variable equal to one if a child is enrolled at a primary school, middle school, secondary school, or higher secondary school currently. We collapsed the ASER data at the district level. Before collapsing the data, we kept observations aged between 4 and 16. The regression includes district and year fixed effects. Standard errors are clustered at the state level. We do not apply district weights from synthetic DID. Confidence intervals are at the 95 percent level.