Impact of Rural Credit on Household Welfare: Evidence from a Long-Term Panel in Bangladesh

by

Authors[1]

MD. Alamgir Hossain (**Corresponding author**)

Deputy Director, Accounts and Budgeting Department, Bangladesh Bank.

Address: Room No. 805-A, Floor-8, Accounts and Budgeting Department, Bangladesh Bank, 15, Motijheel C/A, Dhaka 1000.

Cell No: +8801710766872, Email: malamgir.hossain@bb.org.bd

Abdul Malek Mohammad
Associate Professor, Faculty of Humanities and Social Science, University of Tsukuba.

Address: Room No. 8A406, University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki-305-8571, Japan.

Cell No. +817038106198, Email: malekr25@gmail.com

and
Zhengfei Yu
Assistant Professor, Graduate School of Humanities and Social Science, University of Tsukuba, Japan

Address: University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki-305-8571, Japan.

Phone No. +81298534075, Email: yu.zhengfei.gn@u.tsukuba.ac.jp

[1] We thank the Economics Professors specially Hisahiro Naito and Yuko Nakano and Scholars at Program in Economics and Public Policy (PEPP) at University of Tsukuba, Japan for their helpful comments during PEPP seminars, and ANM Mahfuzur Rahman, Hasib Reza and Colleagues at Socioconsultant for answering our queries on data preparation, ADB for funding scholarship. Finally, we thank Abdul Bayes and late Mahabub Hossain for granting access to the dataset.

Abstract

Access to rural credit has long been considered a potential solution to ease liquidity constraints and improve household welfare in Bangladesh. Earlier studies on rural credit mostly focused on the impact of microfinance; however, the available results could not provide conclusive findings. Evidence on the long term impact of different credit sources, namely, banks, microfinance institutes, and informal channels, is also limited. Using a nationally representative multipurpose five-round (1988, 2000, 2004, 2008, and 2014) panel datasets we provide evidence for the long-term impact of different rural credit sources on household welfare indicators. Results suggest that access to rural credit from any source has no significant impact on the increase in the household economic welfare in the long term. The impact estimates are found to be consistent across different econometric specifications, implying the robust internal validity of the study results.

Key words: Long-term impact, panel data, rural credit sources, rural households, economic welfare.

JEL Codes: 012, Q14, I31 and C33

Introduction

In many developing countries, access to rural credit has long been considered a potential solution to the liquidity constraints of households that fail to develop livelihoods and improve their welfare (Lin et al. 2019). In Bangladesh, rural households often borrow from formal, quasi-formal and informal sources. Formal credit sources include commercial banks and other formal financial intermediaries in rural areas. Microfinance institutions (MFIs) are considered as a quasi-formal source of credit. Friends, relatives and local money lenders constitute informal credit facilities. If credit can be accessed through any source; such as banks, MFIs or individuals, credit-constrained rural households may become involved in income generating activities (IGAs) and improve household welfare. Formal banking services are yet to cover most rural households for high operating costs and less profit (de Aghion, Armendáriz, and Morduch 2007).Since the late 1980s, with the advent of MFIs, such as Grameen Bank and extended agricultural loan support from agricultural banks, rural people's credit demand has been mitigated to a certain extent. However, the importance of money lenders and other informal sources exists in rural households, even with higher interest rates, due to their convenient accessibility (Manig 1996, Mallick 2012). Microcredit, the basis for the Nobel Peace Prize in 2006,which is also a great innovation in easing the credit access for the poor people and a pathway to leave poverty, has been a debatable issue in recent years because of its differential impact on various welfare outcomes (Banerjee et al. 2015, Banerjee, Karlan and Zinman, 2015).

Rural credit, especially microcredit, has been established to be successful in many parts of the world. Many researchers and scholars globally have examined the causal effect of microcredit on the welfare indicators of rural households. However, informal credit and other non-MFI credit sources have largely been unexplored. Thus far, none of the randomized experiments has determined any significant positive impact of microcredit on household income (Angelucci, Karlan and Zinman 2015, Augsburg et al. 2012, Banerjee et al. 2015, Hossain et al. 2019, Karlan and Zinman 2011, Tarozzi, Desai and Johnson 2013). Some studies have established significant results on borrowers' solvency and poverty measures (Imai and Azam 2012, Khandker 1998, 2005, Rui and Xi 2010, Tedeschi 2008, Zaman 1999), while others (Diagne and Zeller 2001, Shaw 2004) fail to locate any impact on poverty. The impact of microcredit on various household welfare measurements has also been overestimated (Banerjee et al. 2015).

The use of long-term panel data for impact evaluation has also been suggested by numerous researchers (Banerjee et al. 2015, Banerjee, Karlan and Zinman 2015, Islam 2011, Kabeer 2005, Khandker 2005, LaLonde 1986). Most of the previous microfinance studies were unable to control for fungibility (Hulme 2000, Khalily 2004, Pitt and Khandker 1998) which may overestimate the results. The failure to consider other close substitutes of MFIs, such as formal and informal credit, has been regarded as one of the challenges in evaluating microcredit programs (Banerjee et al. 2015, Banerjee 2013). Owing to the lack of longer-term household-level panel data, there has been no evidence of whether rural credit access has sustainable welfare impacts. In addition to contributing to the continuing debate on micro-credit impact, our objective is to evaluate the impact of different credit sources on household welfare from a long-term (three decades) perspective.

We use a widely used (Mahmud, Sawada and Tanaka 2021, Kikkawa and Otsuka 2020, Kikkawa, Matsumoto and Otsuka 2018, Balagtasa etal 2014, Hossain, Rahman and Estudillo 2009, Hossain 2007, Nargis and Hossain 2006) long term panel dataset, recently known as the Mahabub Hossain (MH) panel survey data (Gautam and Faruqee 2016). This dataset was earlier collected by the Bangladesh Institute of Development Studies (BIDS), International Rice Research Institute (IRRI) and BRAC. The data was collected from a nationally representative sample following a multi-stage (districts-unions-villages-households) random sampling technique from 62 villages in Bangladesh. The original sample consisted of 1,231 households in 1988, 1,872 in 2000, 1,927 in 2004, 2,010 in 2008, and 2,846 households in 2014.

We use a household-level panel fixed-effect model to estimate the impacts on different outcome indicators. The results suggest that access to rural credit from any source has no significant impact on the increase in household economic welfare in the longer term. However, in the shortrun, access to bank credit increases access to rented-in land, improves rice yield, and enhances girls' school enrollment among rural households. As a by-product of our study, in line with the theory of dynamic incentives for microfinance borrowers (Shapiro 2015), we find a long-term association between households and MFIs.The impact estimates are found to be consistent across different model specifications, implying robust internal validity of the study results.

The remainder of this paper is organized as follows: We present an overview of the rural credit market in Bangladesh, followed by a description of the sampling design, data and a summary of the statistics and empirical strategies. Finally, the regression's results with a robustness check are presented, followed by a conclusion and an indication which can be used for future research.

Overview of the Rural Credit Market in Bangladesh

Bangladesh's rural credit market consists of formal, quasi-formal and informal borrowing sources. Agricultural banks, such as Bangladesh Krishi Bank (BKB), Rajshahi Krishi Unnoyan Bank (RKUB), state-owned commercial banks and other private scheduled banks are the main sources of formal credit. In contrast, microcredit from MFIs is known as a quasi-formal source (Hasan and Malek 2017). Village people also rely on informal sources, such as moneylenders, landlords, owners of sharecropped land, businesspersons, relatives, and friends. However, the demand for informal loans declines with the spread of MFIs in the village credit market (Berg, Emran and Shilpi 2013).

At present, 60 scheduled banks, five non-scheduled banks and 34 non-bank financial institutions operate throughout Bangladesh (Bangladesh Bank Website 2021). According to the Central Bank, the number of rural bank branches should be a minimum of 50% of the total of new branches approved in a given calendar year. Currently, the total number of bank branches is 10588 of which 5452 branches are in urban areas and 5136 are located in rural areas. Only 10.30% of the total of formal banking loans and advances have been disbursed through urban branches (Bangladesh Bank 2020). Most banking activities in rural areas focus on savings but not on credit accounts (Islam and Mamun 2011). A comparison of loan disbursements by the urban and rural branches of formal banking is demonstrated in Annex Figure 1. Loans and advances in urban branches have expanded at an increasing rate since 2000, with a sudden increase in 2011, due to an increase in government borrowing from the banking sector, while total credit disbursement by rural branches observed slow growth. The lack of a large loan demand, a high operating cost per loan and smaller deposits make rural branches less profitable and borrowing costs higher for clients, that induce banks to concentrate only on urban areas (de Aghion et al. 2007). According to Figure 1, borrowing

from commercial banks indicates a declining trend, while MFI borrowing demonstrates an

increasing trend over the last 25 years.

(Figure 1 here)

In 1959, Akhter Hameed Khan, a social scientist, initiated "Comilla Model" for rural advancement which failed, due to inefficient control and lack of a donor fund(Berg, Emran and Shilpi 2013, Alamgir 2010).They added that the founder of Grameen Bank Muhammad Yunus and the late Fazle Hasan Abed of BRAC, the largest nongovernmental organization (NGO), which originated in Bangladesh, learnt some lessons from this failure. In addition, they adopted a more efficient and centralized means of control and a new credit delivery channel targeting the poor without collateral. Grameen Bank was recognized as an independent bank in 1983 and received the Nobel Peace Prize together with its founder in 2006 for their contribution to social development and the rural economy. Following the approach and success of Grameen and BRAC, many other MFIs have evolved over the years and are associated with diversified social programs to connect to the poor in rural areas. According to the Microcredit Regulatory Authority (MRA), Bangladesh has more than 30 million borrowers of microcredit, which is the highest number in the world after India. A total of 783 MRA-registered MFIs with 17120 branches operate mostly in rural areas. The total microcredit disbursement until 2017 by MFIs, including Grameen Bank, Government projects, Commercial banks, and other members of MRA, was 1313.67 billion Taka (Annex Figure 2). Approximately 91% of borrowers in the microfinance sector are women in Bangladesh and 40% of the total loans are provided for agricultural purposes.

In the earlier days, the urgent credit requirements of rural households were mainly served by Mohajons (money lenders) and landowners, due to the lack of formal sources of credit. These Mohajons, also called "usurious monopolists," charged exorbitant rates of interest for lending money. The lack of the required collateral for formal credit and convenient accessibility of informal credit resulted in the latter being sustainable over a period of decades, despite charging a 100-120% interest rate per annum (Berg, Emran and Shilpi 2013). This form of borrowing mostly occurs without legal paperwork, is sometimes inaccurate and may have a fraudulent intension; driving people into absolute poverty commitments that sometimes drive them into acute poverty (Mudahar and Ahmed 2010). Our estimation suggests that the share of informal credit has been reduced over the years in rural areas, with an increase in microfinance program coverage and spread of loans (See Annex Figure 3).

Sampling design, data description and summary statistics

As mentioned earlier, we used a five-round panel dataset (1988, 2000, 2004, 2008 and 2014) from the Mahabub Hossain (MH) survey. The data were earlier collected by the Bangladesh Institute of Development (BIDS), the International Rice Research Institute (IRRI), and BRAC. The first round survey was conducted in 1987-1988 as a component of the "Livelihood Systems in Bangladesh" project. Detailed information on farm and non-farm activities, borrowing, income and expenditure, poverty, resource ownership and other household and village-level characteristics are collected.

It is a panel-structured survey covering 62 districts out of 64 districts (in total) in the country. The sample villages and households are selected based on a multistage random sampling method using socio-economic indicators of each district (Hossain, Rahman and Estudillo 2009, Rahman and Hossain 1995). During the census period, due to administrative problems, two villages were dropped, and on average, 153 households` data from each of the remaining villages were collected. Based on the land tenure and ownership from all households in the villages, households were classified into four groups (rich, solvent, poor, and ultra-poor) for stratification following the participatory rural appraisal (PRA) approach. From each of the 64 villages, 20 households were randomly selected in the first round in 1988, resulting in a total of 1280 households being surveyed.

The same villages were surveyed again in 2000, 2004, 2008 and 2014 to collect data from the original households and their descendants. Over the years, many households were divided into multiple new households (e.g., for marriage), and some also permanently migrated. To address sample attrition and keep the sample representative of the population, some new households were added in each round. In 2000, a second-round survey was conducted on 1880 households. The third-round survey was conducted in 2004 on 1930 households and in the fourth-round, the sample comprised of 2010 households. In the final round of the survey (in 2014), the total sample size was 2846, including the households present in the first four waves and their offshoots.

To conduct the panel data analyses, we first created a balanced panel dataset of 804 identical households. We determined that some households moved to and from other villages. To control this in the second stage, we drop those households, and finally, we are left with 791 households that are present in all five rounds of the survey. To describe the summary of the statistics, we use only those 791 consistent households, as depicted in Table 1.

(Table 1 here)

Table 1 indicates that over the study period, the average household size, male headships in households, land owned by households, working members of households and farm size decreased. In contrast, the household members' average age, educational level, migration, and access to electricity improved gradually from 1988 to 2014. This represents the rural development in terms of education, migration, life expectancy and the access to electricity. Due to the scarcity of the land and the nature of the law, the average land ownership and farm size will be reduced with the increasing number of households.

The main outcome variables that measured household welfare are presented in Table 2. In rural areas, households with labor forces and bullocks for cultivation try to access more land to cultivate crops. They can take land as rented-in from others. Rented-in land by households has increased from 1988 (0.13 hector) to 2014 (0.16 hector) as compared to total land owned by a household. The total land owned by households declined from 0.70 to 0.40%

over the survey periods (Table 1). Although land ownership decreased, rented-in land increased slightly. Because of green revolution technologies in Bangladesh, agricultural productivity increased exponentially and modern rice variety adoption continued to replace traditional varieties. In 1988, 47% of the total rice yield (780 kg per household) used the traditional varieties, whereas 93% of the rice production (1,652 kg per household) adopted the modern variety in 2014.

(Table 2 here)

Household income, which is the main indicator of welfare, has been reported for each of the five waves. Here, all monetary figures have been adjusted based on the CPI index (base year 2010), which is obtained from IMF statistics. From the first round, the average total income continued to increase through 2014, with a slight decrease in 2000 and 2004, rising to 1,47,821 Taka from 1,20,428 Taka in 1988. The CPI adjusted income amounts were reduced by 2% in 2000 from 1988 and 5% in 2004 from 2000. The average total income per household indicates an increase of approximately 13% in 2008 from 2004 and 16% in 2014 from 2008. Household income from crop cultivation, total agricultural income, and wage income indicated a downward trend, while business income and remittance inflows have increased over the years.

During the survey period, rural poverty was reduced by almost half. A poverty status indicator is calculated using the absolute poverty line income, as per the FAO norm (Annex Table 1). Households who are unable to incur the minimum required food (2,110 calories of food per head) and non-food expenses (30% for non-foods) are treated as absolute poor or otherwise non-poor.

School enrollment[2] for an eligible child (more than five years old children) is a mandatory pre-requirement to develop an educated society. In rural areas, where acute poverty prevails, households find it difficult to send their children to school because of financial difficulties and unawareness. Whether a person attends school is the main determinant of school enrollment. Of the total number of boys and girls, the percentage of students attending school is the rate of enrollment for each gender. The school enrollment rate for boys has increased from 64.5% to 96.7% over the years. Initially, the girls' school enrollment rate was less than that of the boys; however, this trend was reversed in 2014.

---

[c]Enrollment rate = (number of children attend to school/total number of kids in household) × 100To calculate enrollment variables, only children aging from six to 10 years of age have been considered as school enrollment rate in this age group.

Empirical Strategies

To measure the welfare effect, we compare the outcomes between credit takers and similar non-credit takers. However, a simple comparison is questionable, due to the non-random credit disbursement, self-selection bias, fungibility and other unobservable factors that affect credit participation and household welfare (Bao Duong and Izumida 2002, Islam 2011, Khalily 2004, Khandker and Rashidur 1999, Khandker 2005, Pitt and Khandaker 1996, 1998, Quach, Mullineux and Murinde 2005). The household credit participation decision is highly influenced by its member's capacity to repay, entrepreneurship skills, latent abilities, and some other unobserved behaviors. To address these issues, we use a household-level fixed effect model to control for unobserved factors, such as individual-or village-level heterogeneity that may be correlated with independent variables.

Our first set of regression equations is as follows, with k=0, 1 and 2, respectively:

$$\boldsymbol{W_{it} = \beta_0 + \beta_1 C_{i(t-k)} + \beta_2 X_{it} + \delta_t + \alpha_i + \varepsilon_{it}} \qquad (\mathbf{1})$$

Where W_{it} represents the welfare indicators (for example household income) for household i at time t and X_{it} is a vector of the household and village level observed characteristics with the relevant control variables. In addition, $C_{i(t-k)}$indicates household i's credit participation from any source in the current period if k = 0, previous period if k=1, or two periods ago if k=2, $\delta_t$and $\boldsymbol{\alpha}$ denote the time fixed effect and household fixed effect. The coefficient $\beta_1$measures the effect of any credit access (in the current or previous periods) on the outcome variables and $\varepsilon_{it}$is the error term.

Robust standard errors were clustered at the household level. Household and village level attributes X_{it} contain the total land owned by household (hector), farm size (hector), age of household head, age squared, gender of the head, education of the head (schooling years), education square, highest educational attainment from household (schooling years), household size (number of members), total number of workers in the household, migration status and access to electricity are used as control variables.

We then conduct a more detailed analysis of the effect of the credit sources by replacing $\boldsymbol{C_{i(t-k)}}$with three indicators for credit sources: Bank credit, MFI credit and informal credit. This leads to the second set of regression equations:

$$\boldsymbol{W_{it} = \beta_0 + \beta_{11} Bank_{i(t-k)} + \beta_{12} MFI_{i(t-k)} + \beta_{13} Informal_{i(t-k)} + \beta_2 X_{it} + \delta_t + \alpha_i + \varepsilon_{it},} \qquad (\mathbf{2})$$

where $\boldsymbol{Bank_{i(t-k)}, MFI_{i(t-k)}}$, and $\boldsymbol{Informal_{i(t-k)}}$denote household i's access to the credit provided by banks, the MFI, and informal channels. The coefficients β_{11}, β_{12}, and β_{13} capture the effect of each credit source on the household's outcome.

The estimates of regression equations (1) and (2) for the different outcome variables are presented in Tables 3–7. The outcome variables we consider include rented-land, rice yields, household income, poverty reduction and child school enrollment. In each table, columns (1) to (3) correspond to k=0,1 and 2. Panel A reports the estimates of $\beta_1$in regressions (1) and Panel B presents the estimates of β_{11}, β_{12}, and β_{13} in regressions (2).

Regression results and discussion

Main Results

Impact on rented-in land

Rural credit-constrained households are likely to ease their liquidity problems through formal or informal borrowing. Therefore, credit access can encourage rural households to engage more in farm activities. In the village area, landless or land-deficient households require financial capital for the permission to cultivate land by way of obtaining land as rented-in. Farmers usually pay a fixed amount of rent before growing crops on other land.

Table 3 summarizes the impact of credit access on rented-in land estimated from regressions (1) and (2).Column (1) of Panel (A) indicates that current year access to any credit increases land obtained as rent by around 17% as compared to non-borrowers. Column (1) of Panel (B) further finds that only credit from the formal banking institutions (increases rented-in land by

54%) is the main catalyst. This is probably because the agricultural loan size from commercial banks: BKB and RKUB are usually higher than MFIs and other informal sources. As a result, credit from sources other than banks may not be sufficient for a household to rent more cultivable land.

(Table 3)

Columns (2) and (3) suggest that MFI and informal borrowers tend to lose their rented-in land after the first and second rounds of the survey. One-period-lagged informal credit has a negative impact (rented-in land reduces by 37.5%) and two-period-lagged MFI borrowers take less land (32%) from the tenancy market as compared to non-borrowers.

The intervention of agricultural microcredit for tenant farmers increases the rented-in land under leasing or sharing cropping, albeit not significantly (Hossain et al. 2019). This study determines similar results for the microcredit impact and additionally discovers that in the long term, it may have negative impacts. The supply of land is limited and many unobservable factors, except financial liquidity, play an important role in this case. This tenancy market influences agricultural production; while contrarily, other forms of inflow (profit, income and remittances) influenced by participation may also contribute to the tenancy market.

Impact on rice yield

To cultivate rice, the main staple food in Bangladesh, approximately 67% of the total cultivated area is used (Hossain et al. 2019), accounting for 75% of the total crop production (Talukder and Chile 2014), whose production cost is often mobilized from the rural credit market. Therefore, we used the farm rice yield as a measure of the agricultural productivity. The impact of current and lagged credit on the total rice production by a household has been estimated.

Table 4 summarizes the results of the current (latest) and previous credit access on rice yield-controlling household and village characteristics, using household fixed effects and year fixed effects. Access to any credit does not have any significant impact on households' rice yield, not only in the latest period but also in earlier periods.

(Table 4 here)

If the credit access is disaggregated into three main sources, then it is established that the significant positive impact of the current credit participation on household rice yield is associated with only commercial bank credit. Bank credit increases the total rice yield by 61%. This result is consistent with Miah et al. (2006), who studied RKUB and GB loans and noted that farmers use commercial bank loans more than microcredit for rice production and rice yield increased by 1.21, as compared to non-borrowers. However, in the longer term (using first and second credit lags), the commercial bank credit impact is not sustained and no other credit source could increase the rice yield in the longer term.

In every season, farmers require financial capital to prepare the land and purchase material inputs. A convenient agricultural loan facility may assist households in increasing their farm rice yield. From the microcredit literature, we learned that borrowing farmers tend to adopt modern technology, HYV seeds, improved fertilizers, and other inputs, which could increase technical efficiency and productivity. The adoption of new technologies in agriculture and increased crop yield through credit access has been studied by many scholars worldwide, including experimental studies (Hossain et al. 2019, Abate et al. 2016, Abdulai and Huffman 2005, Anang, Bäckman and Sipiläinen 2016, Bao Duong and Izumida 2002, Binam et al. 2003, Chandio et al. 2018, Croppenstedt, Demeke and Meschi 2003, Girabi and Mwakaje 2013, González 2014, Isham 2002, Javed et al. 2006, Miah, Alam and Rahman 2006, Rahman, 2011, Islam, Sumelius and Bäckman 2012). However, using long-term panel data, we did not locate any evidence that microcredit increases the farm rice yield.

Our results suggest that current year commercial bank credit increases MV rice yield, although MFI and informal credit participation do not have any impact on traditional or MV rice yields. However, we do not note any impact of one lagged credit on rice yield except MFI credit access (30% increase of the traditional variety rice yield at a five percent significance level) and log of the loan amount (at a 10% level of significance). If is because the MFI loan might have been used for alternate purposes (working capital for other crops and small businesses). In addition, for the longer term, we also do not determine any consistent impact of the credit amount, which supports an increase in the household rice yield.

Impact on household income

Most of the rural household income sources are not restricted to one income source but rather multiple income sources, which helps them to smoothly run the consumption and address shocks. The major components of household income are crop income, non-crop farm income, wage income, business income and remittance income. Therefore, any individual measurement of an income component is likely to lack accuracy, therefore, it is optimal to consider all the related income sources. The impact of credit access on different components of household income using a five-round panel dataset was regressed separately, as shown in Annex Table 2.

Access to any credit source increases the income from crops and businesses but reduces the remittance earnings for the borrower as compared to non-borrowers, as borrowers engage in agriculture and self-employment activities instead of migrating. Bank and informal credit do not have any impact on any of the components of household income, whereas solely MFI credit increases agricultural (crop and non-crop farm income together) and business income. However, it is also important to estimate the impact on total household income, as presented in Table 5.

(Table 5 here)

Using the fixed effect models (1) and (2), we noted consistent results with previous studies where no experimental study and most other non-experimental studies failed to locate any significant impact on the increasing household income. Access to any credit for both the current year and lagged credit does not influence the total income. When the credit impact is segregated into bank, MFI, and informal credit, we also do not establish any evidence that proves that access to any credit source has an impact on the total household income.

In addition to total household income, analyzing different components of income, we find that in the short term access to any credit increase crop and business income but reduce remittance income significantly. Differential impact indicates microcredit as the main underlying reason for the rise in agriculture and business income. Surprisingly, these impact estimates are not consistent and also negative in the long term for second credit lag. That means though MFI credit can be initially helpful in agriculture and business but in the longer period this does not sustain. Whereas, wage income for the households who access to bank credit increase significantly in the long term instead of increasing other components of income. This indicates improper utilization of agriculture and SME loans by the rural households.

Impact on poverty reduction

Access to credit facilities for rural credit-constrained households improves productivity, smooth income and consumption flows, diversifies other income earning options, generates self-employment and increases other benefits (Khandker 1998, Morduch 2011, Pitt and Khandker 1998, Robinson 2001). As defined earlier, poverty estimates are correlated with household income and expenditure, and this is the ultimate outcome of increasing household welfare. Table 6 depicts the regression results of the impact of credit on poverty using household-level panel fixed effects.

(Table 6 here)

During the survey period (1988-2014) the rural poverty status was reduced from 0.60 to 0.38 where poor is given the value of one and non-poor is given the value of 0. Whether credit access played any role in reducing poverty during the study period is necessary to be analyzed. Column one of the fixed effect regression demonstrates that the current year access to any type of credit reduces household poverty, albeit not significantly. In addition, credit from banks, MFIs, or informal sources (panel B) do not assist rural households in relieving them of poverty. In columns two and three, the longer-term impact (first and second credit lags) estimates are presented. Similar to household income, credit access in the longer term does not reduce poverty significantly, not only for any credit but also for banks, MFIs, and informal sources. For short-and long-term banks, informal credit is not established to significantly reduce poverty.

Our findings are consistent with that of the previous experimental studies on microfinance, which did not determine any positive impact on poverty reduction (Angelucci, Karlan and Zinman 2015, Attanasio et al. 2015, Augsburg et al. 2012, Banerjee et al. 2015, Crépon et al. 2015, Karlan and Zinman 2011). Diagne and Zeller (2001) and Shaw (2004) also indicated similar results using non-experimental data.

Impact on children's school enrollment

Children's school attendance is related to household income, distance to school and many other factors. Due to government and non-government initiatives regarding compulsory primary education, there has been a significant improvement in children's schooling outcomes for both boys and girls. In particular, the girls' education scenario changed substantially over the study period. Table 7 summarizes the results of both girls' and boys' school enrolment.

(Table 7 here)

Access to any credit increases girls' school enrolment by around five percent. Boys' school enrolment decreased by two percent, although the difference was not statistically significant.

After the first or second round of the survey, changes in access to credit did not change school enrollment significantly for both boys and girls.

However, the differential impact of various credit sources (panel B) indicates that only borrowing from formal banking institutions influences girls' school enrollment rate (10%), whereas MFI and other informal credit participation do not. This is consistent with previous microfinance studies (Banerjee et al. 2015, Morduch 2011),which did not establish any significant impact. Moreover, this article includes the additional concepts of longer-term impact of microfinance, banks and informal credit on children's school enrollment. Using household-level fixed effects, we observe that changes in credit access from any source did not change the enrollment rate for both boys and girls.

Dynamic incentives of microfinance

Microfinance participation has been increasing since its inception and unlike others, we do not locate any convincing evidence of increasing household welfare. We studied all major sources of borrowing and noted that commercial banks and informal borrowers are unstable in progressive credit taking, while microcredit clients adhere to the same source. When a borrower does not default on the current loan and adheres to the same source to obtain a large loan in the future, it is known as a dynamic incentive. Shapiro (2015) develops a new model on dynamic incentives of microfinance, where he determines that the borrower's expectation of future loans does not assist with loan repayment, and that it may have a negative effect in the case of double-dipping.

Using the five rounds (1988-2014) MH dataset, we estimated the dynamic incentives of MFI credit. Whether the household's previous year credit access from microfinance has any significant impact on next rounds of borrowing is estimated by using cross-sectional datasets and the following equation:

$$C_{ijk} = \beta_0 + \beta_1 \sum_{\mathrm{k}=2}^{\mathrm{k}=5} C_{ij(k-1)} + \beta_2 X_{ij} + \varepsilon_{ij} \qquad (3)$$

where C_{ijk} indicates access to MFI credit (borrowers=1 and non-borrowers=0) for household i in village j at survey year k. Here, k represents second to fifth rounds (1988, 2000, 2004, 2008, and 2014). Thus, $C_{ij(k-1)}$ is the previous round that takes access. If k takes the value of 2014 (fifth round), then k-1 is the previous round that is 2008 (fourth round). X_{ij} is a vector of household level observed characteristics with the relevant control variables, $\beta_1$measure the effect of the last rounds of MFI credit access on the current MFI credit-taking decisions and $\varepsilon_{ij}$is the error term.

In 1988, only a few households (9% of the borrowing households) participated in the microcredit program, which is the reason for first-round credit access not providing an adequate rationale for the following round. However, households who participated in the MFI program in 2000 had 29% more probability than others to borrow credit from any MFI in 2004, 19% in 2008 and 12% in 2014.

(Table 8 here)

MFI credit access in 2004 and 2008 resulted in the same significant outcome for the subsequent rounds. This establishes that the progressive lending concept that borrowers keep borrowing from the same sources and do not default due to their expectation of obtaining continuous and larger loans in the future. Such results are consistent with Mahmud, Sawada and Tanaka 2021).

Robustness check

The impact of rural credit participation on household welfare outcomes does not depend solely on previous credit access. Present credit participation from different sources may also be a significant cause that should be controlled to identify the segregated impact of both present and past estimators. For more robust results, we control for present credit access, where time and household fixed effects are also applied. Using the first credit lag (Annex Table 3) and second credit lag (Annex Table 4), we find no consistent results demonstrating the long-term impact of any credit participation that may improve household welfare. Though rented-in land and rice yield indicate negative coefficients, the first credit lag is used; however, this does not persist when we use the second credit lag.

In addition, we use an unbalanced panel dataset for all rounds (2,885 observations), with the same household-level fixed effect estimation (Annex Table 5). The results suggest that the previous year's access (second credit lag) to any credit does not have an impact on any of the welfare indicators. These results are consistent with our main estimation. MFI credit appears to decrease the household income in the long term; however, the results are not consistent when different lags of credit are used. Therefore, in the longer term, rural credit access cannot contribute to the livelihoods of rural households by increasing income, reducing poverty, or any other improvement in the household welfare indicators.

Moreover, in addition to first and second credit lags, we also use third and fourth credit lags for the longer term impact analysis. Using third lag, in annex table 6, we see results are consistent with previous analysis except reduction in rented in land and boys' school enrolment rate by informal credit participation. Impact estimates of fourth credit lag (Annex table 7) also do not confirm long term sustainable impact of different credit sources on household welfare. So in the longer term, rural credit access cannot contribute to livelihoods of the rural households by increasing income, reducing poverty or any other improvement of household welfare indicators.

Summary and Conclusion

The rural credit market of Bangladesh has changed significantly over the past decade with the central bank's directive regarding agricultural loans and rural branches, as well as microfinance innovation, especially for the poor. We study the impact of various credit sources, including credit accessibility, for the appropriate formal or informal sources on the different household welfare indicators. The study attempted to contribute to the ongoing debate on the impact of microcredit on different outcomes and to estimate the long-term effect of rural credit access from different sources using a true-panel dataset. A five-round longitudinal survey (1988-2014) for a period of 25 years has been used. We apply a household-level panel fixed effect to examine the changes in the household welfare indicators within households, whose credit participation changes over time.

The results of credit access are inconclusive. Overall, credit access does not have any significant impact on the total household income, poverty status, boy's school enrollment and rice yield in the short term. The current year access to bank credit increases households rented-in land, rice yield and girls' school enrollment; while microfinance may increase the income from agriculture and business. Using credit access lags (first and second credit lags), we estimate the long-term impact, which is the main objective of our study. The previous round of overall credit access does not increase the rural household welfare in the long term. When different sources of rural credit are used as explanatory variables, we note that there is no significant evidence to improve the livelihoods of rural households. Finally, microfinance tends to have dynamic incentives for borrowers, as long-term associations have been determined between households and MFIs.

Microfinance impacts were established to be consistent with all previous experimental studies (Angelucci, Karlan and Zinman 2015, Attanasio et al. 2015, Banerjee et al. 2015, Crépon et al. 2015, Hossain et al. 2019, Karlan and Zinman 2011). It is not feasible to conduct long-term experimental studies on microfinance; however, most of the short-term experimental studies conducted thus far have not found a significant positive impact on total income, poverty, or consumption. In this context, the optimistic expectation of microfinance supporters regarding the increase in household welfare has been defined as overvalued by (A. Banerjee, Karlan and Zinman 2015).

One important indicator of household economic performance is consumption; however, owing to the lack of consistent and detailed expenditure related data for all survey periods, this study could not locate an impact on consumption. Moreover, we do not determine a time-varying proper instrument, which is the independent variable, to estimate more robust results in the dataset. The time gap between survey periods is not consistent, which may contribute to inaccuracy in the average impact. The longest gap was 12 years between the first and second rounds, whereas the smallest was four years.

Identifying the credit demand of rural households and institutional credit innovations to maximize household welfare is required to be a policy concern and it is crucial to identify the underlying factors for which credit is unable to contribute to in the long term. Certainly, rural households generate short-term benefits from credit access; however, they probably do not reinvest for productive purposes or consume the gains, which may be a potential rationale for the absence of long-term impact.

References

Abate, G.T.,Shahidur, R., Borzaga, C. and Getnet, K. 2016. Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter?World Development,84,235–53. https://doi.org/10.1016/j.worlddev.2016.03.003

Abdulai, A. and Huffman. W.E. 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. American Journal of Agricultural Economics,87,645–59. https://doi.org/10.1111/j.1467-8276.2005.00753.x.

Aiko Kikkawa and Keijiro Otsuka. 2020. The changing landscape of international migration: evidence from rural households in Bangladesh, 2000–2014, Oxford Development Studies, DOI: 10.1080/13600818.2020.1790509.

Joseph V. Balagtasa, Humnath Bhandarib, Ellanie R. Cabrerac, Samarendu Mohantyc and Mahabub Hossain. 2014. Did the commodity price spike increase rural poverty? Evidence from a long-run panel in Bangladesh. Agricultural Economics 45 (2014) 303–312.

Hossain, Mahabub. 2007. Technological progress for sustaining food population balance: achievement and challenges. Agricultural Economics, 37 (S1) 161-172.

Nargis, Nigar and Hossain, Mahabub. 2006. Income dynamics and pathways out of rural poverty. Agricultural Economics 35 (Suppliment) 425-435.

Aiko Kikkawa, Tomoya Matsumoto and Keijiro Otsuka. 2018. An Inquiry into the Heterogeneous Outcomes of International Migration: Evidence from Rural Households in Bangladesh, The Journal of Development Studies, DOI: 10.1080/00220388.2018.1539476.

Anang, B. T., Bäckman, S. and Sipiläinen. T. 2016. Agricultural Microcredit and Technical Efficiency. (Online), date retrieved. https://helda.helsinki.fi/handle/10138/233240

Manuela, A., Karlan, D., and Zinman. J. 2015. Microcredit impacts: Evidence from a randomized microcredit program placement experiment by compartamos banco.American Economic Journal: Applied Economics,7, 151–82. https://doi.org/10.1257/app.20130537

Augsburg, B., De Haas, R.,Harmgart, H. and Meghir. C. 2012.Microfinance at the Margin: Experimental Evidence from Bosnia and Herzegovina. SSRN Scholarly Paper ID 2021005. https://papers.ssrn.com/abstract=2021005

Banerjee, A., Duflo, E., Glennerster, R. and Kinnan. C. 2015. The miracle of microfinance? Evidence from a randomized evaluation.American Economic Journal: Applied Economics,7, 22–53. https://doi.org/10.1257/app.20130533

Banerjee, A., Karlan, D. and Zinman,J. 2015. Six randomized evaluations of microcredit: Introduction and further steps.American Economic Journal: Applied Economics,7, 1–21. https://doi.org/10.1257/app.20140287

Banerjee, A.V. 2013. Microcredit under the microscope: What have we learned in the past two decades, and what do we need to know?Annual Review of Economics,5, 487–519. https://doi.org/10.1146/annurev-economics-082912-110220

Bangladesh Bank Website. 2021. date retrieved January 31, 2021.https://www.bb.org.bd/en/index.php/financialactivity/bankfi

Bao, D.P. and Izumida. Y. 2002. Rural development finance in Vietnam: A microeconometric analysis of household surveys.World Development,30, 319–35. https://doi.org/10.1016/S0305-750X(01)00112-7

Berg, C. M., & Shilpi. S.E.F. 2013. Microfinance and Moneylenders: Long-Run Effects of MFIs on Informal Credit Market in Bangladesh. Policy Research Working Papers. The World Bank. https://doi.org/10.1596/1813-9450-6619

Binam, J.N., Kalilou, S., Diarra, I. and Nyambi,G. 2003. Factors affecting technical efficiency among coffee farmers in Côte d'Ivoire: Evidence from the Centre West Region.African Development Review,15,66–76. https://doi.org/10.1111/1467-8268.00063

Chandio, A.A., Jiang, Y., Wei, F. and Guangshun,X. 2018. Effects of agricultural credit on wheat productivity of small farms in Sindh, Pakistan. Agricultural Finance Review,78,592–610. https://doi.org/10.1108/AFR-02-2017-0010

Crépon, B., Devoto, F., Duflo, E. and Parienté,W. 2015. Estimating the impact of microcredit on those who take it up: Evidence from a randomized experiment in Morocco.American Economic Journal: Applied Economics,7,123–50. https://doi.org/10.1257/app.20130535.

Croppenstedt, A., Demeke, M. and Meschi,M.M. 2003.Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia.Review of Development Economics,7,58–70. https://doi.org/10.1111/1467-9361.00175.

de Aghion, B.A., Armendáriz, B. and Morduch, J. 2007. The economics of microfinance. London MIT Press.

Diagne, A. and Zeller,M. 2001. Access to credit and its impact on welfare in Malawi.Washington, D.C. International Food Policy Research Institute.

Girabi, F. and Mwakaje,A.E.G. 2013. Impact of microfinance on smallholder farm productivity in Tanzania: The case of Iramba District.Asian Economic and Financial Review, 227-242 .

González, C. R. 2014. Can micro-finance help small farmers in developing countries improve their livelihoods? A systematic review. Florida:Florida International University.

Hossain, M., Rahman, M. and Estudillo, J. P. 2009. Poverty dynamics in Rural Bangladesh. In K. Otsuka, J. P. Estudillo and Y. Sawada (Eds.), Rural poverty and income dynamics in Asia and Africa (pp. 94–117). London: Routledge.

Hossain, M., Malek, M.A., Hossain, M.A., Reza, M.H. and Ahmed,M.S. 2019. Agricultural microcredit for tenant farmers: Evidence from a field experiment in Bangladesh. American Journal of Agricultural Economics,101,692–709. https://doi.org/10.1093/ajae/aay070.

Hulme, D. 2000. Impact assessment methodologies for microfinance: Theory, experience and better practice.World Development,28,79–98. https://doi.org/10.1016/S0305-750X(99)00119-9

Imai, K.S. and Azam,M.D.S. 2012.Does microfinance reduce poverty in Bangladesh? New evidence from household panel data.The Journal of Development Studies,48,633–53. https://doi.org/10.1080/00220388.2012.661853

Isham, J. 2002. The effect of social capital on fertilizer adoption: Evidence from rural Tanzania. Journal of African Economies,11, 39–60. https://doi.org/10.1093/jae/11.1.39

Islam, A. 2011. Medium- and long-term participation in microcredit: An Evaluation using a new panel dataset from Bangladesh. American Journal of Agricultural Economics,93,847–66. https://doi.org/10.1093/ajae/aar012

Islam, E. and Mamun,S.A. 2011. Financial Inclusion: The Role of Bangladesh Bank. Working Paper WP1101.Research Department, Bangladesh Bank, Dhaka, 21.

Islam, Z.K.M., Sumelius, J. and Bäckman, S. 2012. Do differences in technical efficiency explain the adoption rate of HYV rice? Evidence from Bangladesh. Agricultural Economics Review,13(389-2016-23491), 93-110. https://doi.org/10.22004/ag.econ.253500

Javed, S., Hassan, S., Adil, S.A., Ahmad, A.S., Chattah, W.A. and Nawaz,Z. 2006. Impact assessment of micro-credit programme of PRSP on crop productivity. Pak. J Agri. Sci, 43(3-4), 209-212.

Kabeer, N. 2005. Is microfinance a 'Magic bullet' for women's empowerment? Analysis of findings from South Asia.Economic and Political Weekly,40, 4709–4718.

Karlan, D. and Zinman,J. 2011. Microcredit in theory and practice: Using randomized credit scoring for impact evaluation.Science,332, 1278–1284. https://doi.org/10.1126/science.1200138

Khalily, M.A.B. 2004. Quantitative approach to impact analysis of microfinance programmes in Bangladesh—What have we learned?Journal of International Development,16, 331–353. https://doi.org/10.1002/jid.1081

Khandker, S. R. 1998. Fighting Poverty with Microcredit: Experience in Bangladesh.Fighting Poverty with Microcredit: Experience in Bangladesh.(Online), date retrieved.https://www.cabdirect.org/cabdirect/abstract/19991800156

Khandker, S.F. and Rashidur, R. 1999.The Impact of Farm Credit in Pakistan. Policy Research Working Papers. The World Bank.(Online), date retrieved. https://doi.org/10.1596/1813-9450-2653

Khandker, S.R. 2005. Microfinance and poverty: Evidence using panel data from Bangladesh.The World Bank Economic Review,19, 263–286. https://doi.org/10.1093/wber/lhi008

LaLonde, R.J. 1986. Evaluating the econometric evaluations of training programs with experimental data.The American Economic Review,76, 604–620.

Lin, L., Wang, W., Gan, C. and Nguyen, Q.T.T. 2019. Credit constraints on farm household welfare in rural China: Evidence from Fujian Province.Sustainability,11,3221.https://doi.org/10.3390/su11113221

Madhur, G.,&Faruqee, R. 2016. Dynamics of rural growth in Bangladesh: Sustaining poverty reduction.Washington, DC World Bank Publications.

Mallick, D. (2012).Microfinance and moneylender interest rate: Evidence from Bangladesh. World Development, 40, 1181–1189.

Manig, W. 1996.The importance of the informal financial market for rural development financing in developing countries: The example of Pakistan. The Pakistan Development Review, 35(3),229–239.

Miah, M.A., Kabir, A. K. M., Alam, A. and Rahman,A. 2006. Impact of agricultural credit on MV Boro rice cultivation in Bangladesh.Journal of Agriculture & Rural Development,4,161–168. https://doi.org/10.3329/jard.v4i1.784.

Mahmud, M., Sawada, Y. and Tanaka, M. 2021. Microfinance Competition and Multiple Borrowing: Evidence using Panel Data from Bangladesh. JICA Ogata Research InstituteWorking Paper No 216, January 2021.

Morduch, J. 2011. Does Microfinance Really Help the Poor? New Evidence on Flagship Programs in Bangladesh. In Readings in Microfinance: Reach and Impact. University Press Limited, 323-349.

Orazio, A., Augsburg, B., De Haas, R., Fitzsimons, E. and Harmgart, H. 2015.The impacts of microfinance: Evidence from joint-liability lending in Mongolia. American Economic Journal: Applied Economics,7, 90–122. https://doi.org/10.1257/app.20130489

Pitt, M.M. and Khandker, S.R. 1996. World Bank.Household and Intrahousehold Impact of the Grameen Bank and Similar Targeted Credit Programs in Bangladesh. World Bank Discussion Papers. The World Bank. (Online), date retrieved.https://doi.org/10.1596/0-8213-3594-4

Pitt, M.M. and Khandker,S.R. 1998. The impact of group - Based credit programs on poor households in Bangladesh: Does the gender of participants matter?Journal of Political Economy,106,958–996. https://doi.org/10.1086/250037

Quach, M.H., Mullineux, A.W. and Murinde,V. 2005. Access to credit and household poverty reduction in rural Vietnam: A cross-sectional study. A Cross-Sectional Study. The Birmingham Business School, The University of Birmingham Edgbaston, 1–40.

Rahman, Z. H. and Hossain, M. 1995. Study coverage and methodology. In M. Hossain, B. Sen, & H. Z. Rahman (Eds.), Rethinking rural poverty: Bangladesh as a case study (pp. 28–38). New Delhi: Sage Publication.

Rahman, M.W. 2011. Policies and Performances of Agricultural/Rural Credit in Bangladesh: What Is the Influence on Agricultural Production? SSRN Scholarly Paper ID 1976233. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=1976233

Robinson, M.S. 2001. The Microfinance Revolution. The World Bank. (Online), date retrieved.https://doi.org/10.1596/0-8213-4524-9.

Rui, L.,&Xi, Z. 2010. Econometric analysis of credit constraints of Chinese rural households and welfare loss.Applied Economics,42,1615–1625. https://doi.org/10.1080/00036840701721604

Shapiro, D. A. 2015. Microfinance and dynamic incentives. Journal of Development Economics,115, 73–84. https://doi.org/10.1016/j.jdeveco.2015.03.002

Shaw, J. 2004. Microenterprise occupation and poverty reduction in microfinance programs: Evidence from Sri Lanka. World Development,32, 1247–1264. https://doi.org/10.1016/j.worlddev.2004.01.009

Talukder, D. and Chile,L. 2014. Characteristics of rice cultivation and rural rice market in Bangladesh: Evidence from a survey. Agricultural Economics Review,15, 68-84https://doi.org/10.22004/ag.econ.253683

Tarozzi, A., Desai, J. and Johnson,K. 2013. On the Impact of Microcredit: Evidence from a Randomized Intervention in Rural Ethiopia.(Online), date retrieved. http://repositori.upf.edu/handle/10230/21806

Tedeschi, G.A. 2008. Overcoming selection bias in microcredit impact assessments: A case studyin Peru.The Journal of Development Studies,44, 504–518. https://doi.org/10.1080/00220380801980822

Zaman, H. (1999).Assessing the poverty and vulnerability impact of micro-credit in Bangladesh:...A case study of BRAC. World Bank, Development Economics, Office of the Senior Vice President and Chief Economist, 50.

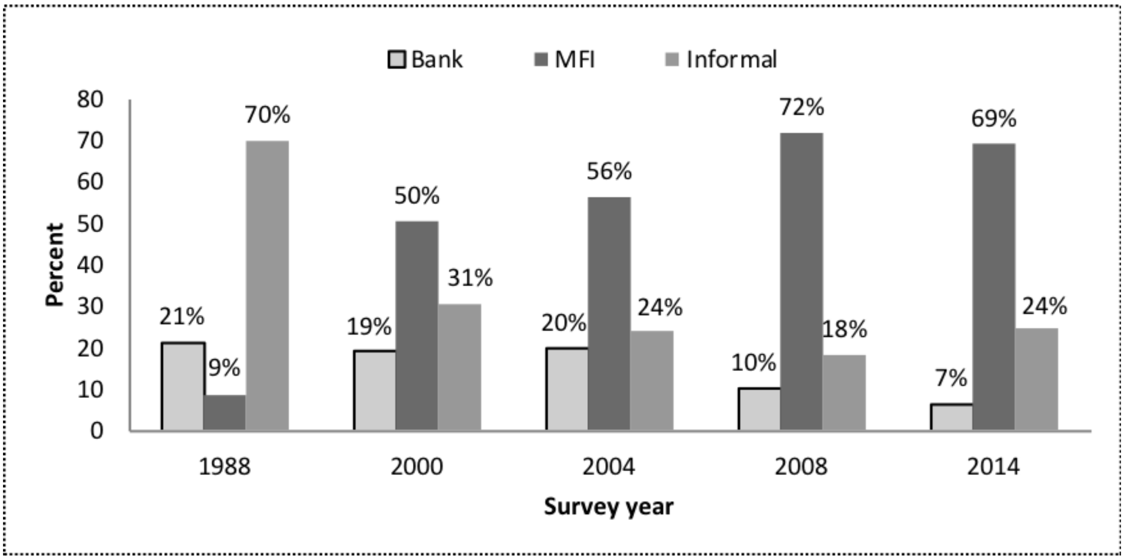


Figure 1. Trend of credit participation by rural households from different sources, 1988-2014.

Source: Author's calculation from five rounds of MH survey datasets.

Table 1. Characteristics of Sample Households, 1988-2014

	1988	2000	2004	2008	2014
Household size (No of members)	6.13	5.59	5.36	5.29	4.60
	(2.89)	(2.52)	(2.31)	(2.35)	(2.01)
Gender of household head (Male=1, Female=0)	0.95	0.94	0.93	0.88	0.84
	(0.20)	(0.22)	(0.25)	(0.31)	(0.36)
Age of household head (years)	41.73	45.90	47.85	49.3	48.1
	(13.96)	(12.41)	(12.75)	(13.7)	(13.5)
Education of head (schooling years)	3.17	3.76	3.98	3.95	4.55
	(3.94)	(4.21)	(4.41)	(4.29)	(4.43)
Highest education by a member of household	4.83	6.89	7.23	7.62	8.89
	(4.27)	(3.92)	(3.90)	(3.67)	(4.41)
Total working member of household	1.71	1.58	1.67	1.68	1.32
	(1.08)	(0.90)	(0.90)	(1.02)	(0.68)
Land owned by household (hector)	0.70	0.58	0.52	0.50	0.40
	(1.04)	(1.02)	(0.87)	(0.88)	(0.73)
Farm size (hector)	0.59	0.41	0.40	0.35	0.31
	(0.97)	(0.68)	(0.76)	(0.60)	(0.55)
Migration (if any member migrated=1)	0.10	0.50	0.21	0.25	0.35
	(0.30)	(1.11)	(0.41)	(0.43)	(047)
Distance to upazila headquarter from village (kilometer)	5.45	5.45	5.44	5.45	5.48
	(3.41)	(3.41)	(3.42)	(3.42)	(3.46)
Electricity Access (village has electricity=1)	0.25	0.49	0.63	0.80	0.88
	(0.43)	(0.50)	(0.48)	(0.39)	(0.32)

Note: The numbers in parentheses are standard deviations.

Table 2. Summary of Main Outcome Variables, 1988-2014

	1988	2000	2004	2008	2014
Rented-in land (hector)	0.13	0.13	0.15	0.12	0.16
	(0.31)	(0.33)	(0.33)	(0.30)	(0.44)
Total rice yield (kg)	1,657	2,065	1,732	1,544	1,652
	(3,316)	(5,943)	(3,017)	(2,829)	(2,873)
Traditional variety	780	151	253	156	102
	(1,656)	(784)	(846)	(922)	(450)
Modern variety	877	1,913	1,478	1,388	1,550
	(2,378)	(5,503)	(2,621)	(2,722)	(2,829)
Total household income(BDT/year)	120,428	118,093	111,569	126,929	147,821
	(175,389)	(174,429)	(144,323)	(167,736)	(175,995)
Crop income	43,002	28,577	30,417	33,098	28,354
	(69,506)	(63,494)	(58,851)	(70,211)	(72,163)
Non-crop income	25,796	21,983	14,837	15,023	24,685
	(37,171)	(36,553)	(33,616)	(33,026)	(39,207)
Wage income	25,205	11,044	13,158	17,796	20,034
	(87,522)	(20,490)	(23,440)	(28,011)	(32,176)
Income from business	10,701	30,456	21,539	16,668	24,958
	(34,215)	(1,21,574)	(63,587)	(57,661)	(65,207)
Income from agriculture	68,798	50,560	51,366	55,937	53,040
	(80,087)	(76,812)	(71,039)	(82,613)	(86,536)
Remittance inflows	9,801	17,460	16,699	27,992	40,425
	(94,526)	(58,992)	(57,747)	(1,00,659)	(1,18,686)
Poverty status (poor=1, non-poor=0)	0.59	0.47	0.41	0.53	0.38
	(0.49)	(0.49)	(0.49)	(0.49)	(0.48)
School enrollment rate for boys (6-10 years)	64.49	90.86	92.39	90.90	96.77
	(45.26)	(27.06)	(25.90)	(28.37)	(17.72)
School enrollment rate for girls (6-10 years)	56.52	91.96	94.86	96.15	98.09
	(47.36)	(26.06)	(21.45)	(18.46)	(13.70)

Note: Numbers in parentheses are standard deviations. All monetary figures are adjusted for inflation using a Consumer Price Index (CPI)of 28.66, 53.91, 64.60, 87.73 and 136.13 for 1988, 2000, 2004, 2008 and 2014 respectively (base year=2010).

Table 3. Impact of Credit on Rented-in Land Using Panel Fixed Effects

Main dependent variable: Log of rented-in land (decimals)	(1) Current credit	(2) 1st credit lag	(3) 2nd credit lag
Panel A: Credit participation dummy from any source(1=yes, 0=no)			
Any credit	0.169*	-0.210**	-0.092
	(0.092)	(0.094)	(0.088)
R-squared	0.122	0.123	0.121
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.544***	-0.110	-0.159
	(0.210)	(0.186)	(0.158)
MFI credit	0.081	-0.122	-0.326***
	(0.109)	(0.117)	(0.122)
Informal credit	0.208	-0.375***	0.192*
	(0.132)	(0.129)	(0.111)
R-squared	0.127	0.125	0.127

Note: Household and village characteristics, such as age, age squared, education, education squared and gender of household head, land owned, household size, farm size, total workers in household, migration status and electricity access are controlled. The results are estimated using the panel data for 791 households. Year and household fixed effects are applied in both panels. Robust standard errors in the parentheses are clustered at household levels, which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1.

Table 4. Impact of Credit Participation on Rice Yield Using Panel Fixed Effects

Main dependent variable: Log of total rice yield	(1) Current credit	(2) 1st credit lag	(3) 2nd credit lag
Panel A: Credit participation dummy from any source(1=yes, 0=no)			
Any credit	0.077	-0.229	-0.075
	(0.146)	(0.153)	(0.146)
R-squared	0.119	0.120	0.119
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.614**	-0.328	-0.202
	(0.287)	(0.319)	(0.254)
MFI credit	0.178	-0.146	-0.373*
	(0.170)	(0.185)	(0.208)
Informal credit	-0.065	-0.250	0.266
	(0.212)	(0.216)	(0.177)
R-squared	0.121	0.120	0.122

Note: Age, age squared, education, education squared and gender of household head, land owned, household size, farm size, total workers in household, migration status and electricity access are controlled. The results are estimated using the panel data for 791 households. Year and household fixed effects are applied in both panels. Robust standard errors are clustered at household levels, which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1.

Table 5: Impact of Credit on Total Household Income Using Panel Fixed Effects

Main dependent variable: Log of total household income	(1) Current credit	(2) 1st credit lag	(3) 2nd credit lag
Panel A: Credit participation dummy from any source(1=yes, 0=no)			
Any credit	0.039	0.034	-0.036
	(0.034)	(0.032)	(0.034)
R-squared	0.204	0.204	0.204
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.054	0.038	0.030
	(0.065)	(0.057)	(0.064)
MFI credit	0.058	0.057	-0.045
	(0.037)	(0.038)	(0.042)
Informal credit	-0.015	0.007	-0.066*
	(0.050)	(0.048)	(0.039)
R-squared	0.205	0.204	0.205

Note: Age, age squared, education, education squared and gender of household head, land owned, household size, farm size, total workers in household, highest educational level by any member, migration status and electricity access are controlled. The results are estimated using the panel data for 791 households. Year and household fixed effects are applied in both panels. Robust standard errors are clustered at household levels which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1.

Table 6. Impact on Poverty Status of Rural Households Using Fixed Effects

Main dependent variable: Household's poverty status	(1) Current credit	(2) 1st credit lag	(3) 2nd credit lag
Panel A: Credit participation dummy from any source(1=yes, 0=no)			
Any credit	-0.029	-0.021	0.020
	(0.024)	(0.022)	(0.022)
R-squared	0.104	0.103	0.103
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	-0.024	-0.017	0.001
	(0.047)	(0.041)	(0.039)
MFI credit	-0.005	-0.037	0.005
	(0.028)	(0.029)	(0.030)
Informal credit	-0.044	0.013	0.043
	(0.034)	(0.033)	(0.028)
R-squared	0.104	0.104	0.104

Note: Age, age squared, education, education squared and gender of household head, land owned, household size, farm size, total workers in household, highest educational level by any member, migration status and electricity access are controlled. The results are estimated using the panel data for 791 households. Year and household fixed effects are applied in both panels. Robust standard errors are clustered at household levels which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1.

Table 7. Impact on Children School Enrollment Using Fixed Effects

Main dependent variable: School enrollment rate for boys and girls aged 6-10 years	Current credit (1)	(2)	1st credit lag (3)	(4)	2nd credit lag (5)	(6)
	Girls	Boys	Girls	Boys	Girls	Boys
Panel A: Credit participation dummy from any source (1=yes, 0=no)						
Log of total credit	4.909**	-2.116	-1.919	-2.905	-2.905	0.086
	(2.460)	(4.498)	(2.389)	(4.526)	(2.057)	(3.549)
R-squared	0.088	0.091	0.078	0.093	0.081	0.090
Panel B: Differential impact (credit dummy for each credit source)						
Bank credit (log)	10.528*	-2.473	-3.019	3.710	-3.467	0.530
	(5.396)	(5.418)	(2.137)	(4.876)	(4.290)	(3.120)
MFI credit (log)	3.410	-2.068	-1.172	-4.317	-2.995	-3.115
	(3.228)	(5.801)	(3.241)	(6.157)	(3.239)	(4.943)
Informal credit (log)	5.619	-0.556	-2.744	-4.908	-1.402	1.799
	(3.462)	(6.265)	(3.070)	(7.240)	(1.954)	(5.158)
R-squared	0.096	0.091	0.079	0.098	0.081	0.093

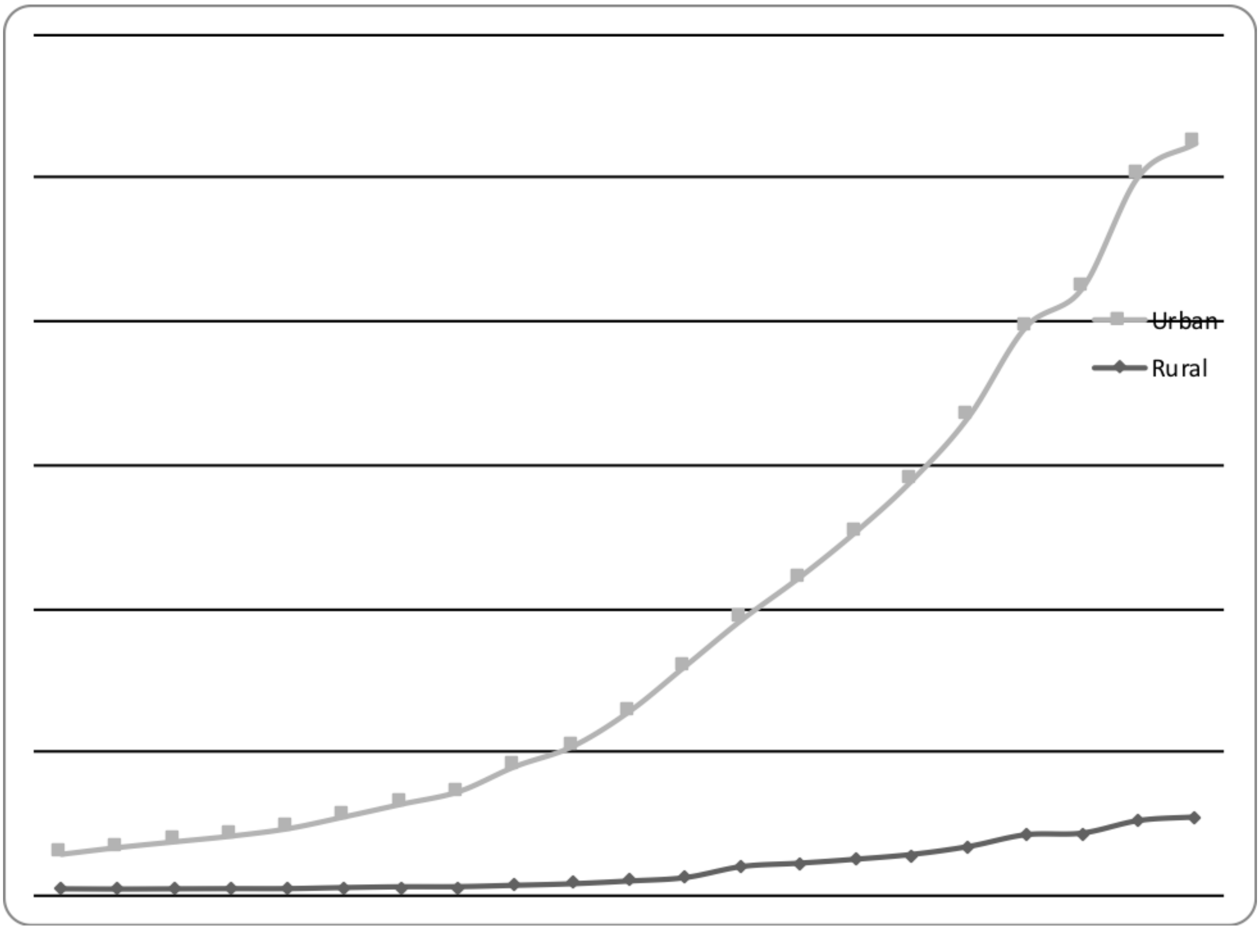
Note: Household and village characteristics such as age, age squared, education, education squared and gender of household head, land owned, household size, farm size, total workers in household, highest educational level by any member, migration status and electricity access are controlled. The results are estimated using the panel data for 791 households. Year and household fixed effects are applied in both panels. Robust standard errors are clustered at household levels which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1.

Table 8. Impact of Previous Microfinance access on Next Round MFI Credit Access

	2000	2004	2008	2014
Independent variables:				
MFI credit in 1988	0.00	-0.02	0.03	0.16
	(0.07)	(0.08)	(0.07)	(0.11)
MFI credit in 2000		0.29***	0.19***	0.12**
		(0.05)	(0.05)	(0.05)
MFI credit in 2004			0.34***	0.18***
			(0.04)	(0.05)
MFI credit in 2008				0.23***
				(0.04)

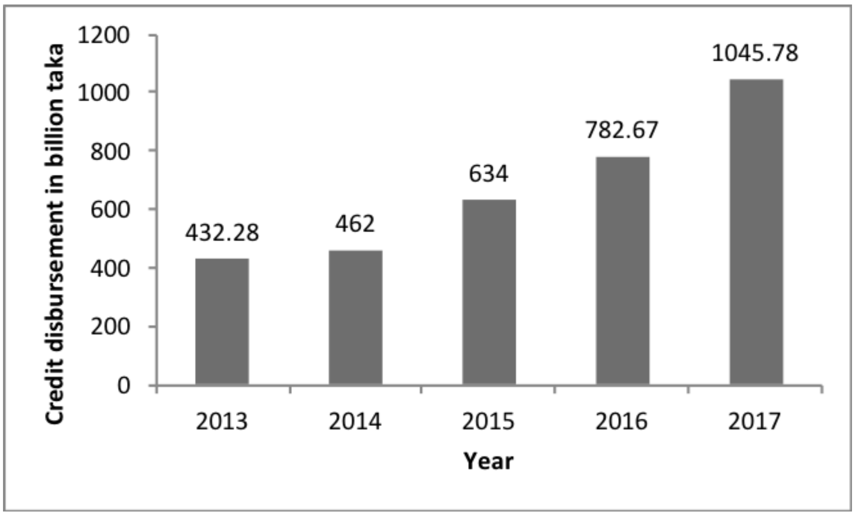
Note: Household and village characteristics are controlled. The results are estimated using the panel data for 791 households. Robust standard errors are clustered at village levels. ***P<0.01, **P<0.05, *P<0.1.

Annex Figure 1. Disbursement of Loans through the Rural and Urban Bank Branches, 2000-2020 in Billion BDT.



Source: Banking Regulation and Policy Department, and Statistics Department, Bangladesh Bank.

Annex Figure 2. Microcredit Disbursement by MRA Registered Institutions, 2013-2017



Source: MRA-MIS Database- 2017

Annex Table 1: Estimates of the Poverty Line from 1988 to 2014

Reference year of survey	Estimated income poverty line (current Taka)
1988	4,609
2000	7,023
2004	8,332
2008	15,194
2014	24,522

Note: Poverty line estimation figures are taken from Hossain and Bayes (2015, 2018).

Annex Table 2: Impact of Credit on Various Components of Household Income Using Panel Fixed Effects

	(1) Crop	(2) Non-crop	(3) Wage	(4) Business	(5) Remittance
Panel A. Access to any credit (1=yes, 0=no)					
Current credit	0.284**	0.178	0.050	0.825***	-0.080**
	(0.127)	(0.117)	(0.228)	(0.212)	(0.036)
1st credit lag	-0.133	0.019	-0.085	-0.157	0.055*
	(0.132)	(0.112)	(0.220)	(0.230)	(0.032)
2nd credit lag	-0.156	-0.150	0.413**	-0.392*	-0.026
	(0.123)	(0.108)	(0.208)	(0.214)	(0.034)
Differential impact (credit dummy for each credit source)					
Panel B: Bank credit dummy (1=yes, 0=no)					
Current credit	0.047	-0.084	-0.240	0.376	-0.026
	(0.214)	(0.238)	(0.459)	(0.460)	(0.071)
1st credit lag	0.254	0.123	0.003	0.157	0.051
	(0.204)	(0.186)	(0.381)	(0.397)	(0.047)
2nd credit lag	0.095	-0.175	0.726**	0.257	-0.084
	(0.165)	(0.153)	(0.336)	(0.406)	(0.056)
Panel C: MFI credit dummy (1=yes, 0=no)					
Current credit	0.297*	0.232*	0.074	1.250***	-0.052
	(0.156)	(0.131)	(0.266)	(0.261)	(0.036)
1st credit lag	-0.121	0.030	-0.059	0.019	0.041
	(0.165)	(0.150)	(0.272)	(0.288)	(0.040)
2nd credit lag	-0.394**	-0.136	0.193	-0.507*	0.043
	(0.182)	(0.162)	(0.295)	(0.283)	(0.040)
Panel D: Informal credit dummy (1=yes, 0=no)					
Current credit	0.238	0.068	0.372	0.014	-0.084
	(0.179)	(0.171)	(0.323)	(0.280)	(0.053)
1st credit lag	-0.252	-0.172	-0.231	-0.346	0.096*
	(0.192)	(0.162)	(0.307)	(0.343)	(0.050)
2nd credit lag	0.062	-0.023	0.283	-0.438	-0.028
	(0.164)	(0.131)	(0.251)	(0.280)	(0.044)

Note: Household and village characteristics are controlled. Year and household fixed effects are applied in both panels. Robust standard errors are clustered at household levels which are presented in parentheses. ***P<0.01, **P<0.05, *P<0.1. Number of observations for all panels are 2,373.

Annex Table 3. Lagged Credit first lag) Impact on Household Welfare Controlling Current Credit Access

Main household welfare indicators	(1) Any credit	(2) Bank	(3) MFI	(4) Informal
Rented-in land (log), in decimal	-0.175*	0.050	-0.122	-0.349**
	(0.098)	(0.188)	(0.119)	(0.137)
Total rice yield (log), in kilogram	-0.322**	-0.167	-0.237	-0.414*
	(0.1616)	(0.345)	(0.195)	(0.231)
Total household income (log), BDT	0.050	0.056	0.077*	0.002
	(0.033)	(0.060)	(0.039)	(0.050)
Poverty status (poor=1, non-poor=0)	-0.033	-0.027	-0.040	-0.002
	(0.023)	(0.043)	(0.030)	(0.034)
Girls school enrollment rate (6-10 years)	-0.342	-0.113	-0.205	-1.207
	(2.614)	(2.808)	(3.543)	(3.286)
Boys school enrollment rate (6-10 years)	-4.412	4.572	-5.551	-5.857
	(4.697)	(3.497)	(6.479)	(7.631)

Note: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at household levels. (***P<0.01, **P<0.05, *P<0.1). No. of observations for all outcomes are 2373 except educational outcome (girls enrollment-772, boys enrollment 570).

Annex Table 4: Lagged Credit (second Lag) Impact on Household Welfare Controlling Current Credit Access

Main household welfare indicators	(1) Any credit	(2) Bank	(3) MFI	(4) Informal
Rented-in land (log)	-0.066	-0.085	-0.318**	0.232**
	(0.090)	(0.159)	(0.126)	(0.112)
Total rice yield (log)	-0.063	-0.104	-0.339	0.266
	(0.150)	(0.256)	(0.216)	(0.181)
Total household income (log)	-0.031	0.042	-0.032	-0.071*
	(0.034)	(0.065)	(0.043)	(0.039)
Poverty status (poor=1, non-poor=0)	0.015	-0.001	0.004	0.038
	(0.022)	(0.040)	(0.031)	(0.028)
Girls school enrolment rate (6-10 years)	-2.236	-1.798	-2.905	-0.743
	(2.003)	(4.060)	(3.318)	(1.896)
Boys school enrolment rate (6-10 years)	0.203	0.458	-2.924	1.767
	(3.494)	(3.255)	(5.155)	(5.143)

Note: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at household levels.(***P<0.01, **P<0.05, *P<0.1). No. of observations for all outcomes are 2373 except for educational outcome (girls enrolment-772, boys enrolment 570).

Annex Table 5: Lagged Credit Impact on Welfare Indicators Using Unbalanced Panel

	Rented in land	Total rice yield	Income	Poverty	School enrolment rate	
					Girls	Boys
Panel A. Access to any credit (lagged credit)						
Any credit	-0.074	0.018	-0.039	0.025	-2.631	-0.104
	(0.082)	(0.139)	(0.032)	(0.021)	(1.916)	(3.404)
Observations	2,885	2,885	2,885	2,885	915	685
R-squared	0.119	0.102	0.206	0.109	0.076	0.084
Panel B: Differential impact (lagged credit dummy for each source)						
Bank credit	-0.144	0.008	0.024	0.006	-3.153	0.150
	(0.147)	(0.245)	(0.060)	(0.038)	(3.772)	(3.035)
MFI credit	-0.30***	-0.294	-0.071*	0.017	-2.793	-3.107
	(0.116)	(0.196)	(0.040)	(0.029)	(3.115)	(4.808)
Informal credit	0.170*	0.299*	-0.040	0.034	-1.346	1.258
	(0.101)	(0.168)	(0.037)	(0.026)	(1.799)	(4.796)
Observations	2,885	2,885	2,885	2,885	915	685
R-squared	0.124	0.105	0.206	0.109	0.076	0.086

Note: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at household levels. (***P<0.01, **P<0.05, *P<0.1). Second lag of credit access is used to see longer term impact.

Annex Table 6: Credit Impact on Welfare Indicators Using Third Credit Lag

	Rented in land	Total rice yield	Income	Poverty	School enrolment rate	
					Girls	Boys
Panel A. Access to any credit (lagged credit)						
Any credit	-0.194*	-0.194	-0.052	0.045	1.696	-7.090
	(0.107)	(0.191)	(0.048)	(0.031)	(3.103)	(8.746)
Observations	1,582	1,582	1,582	1,582	509	353
R-squared	0.318	0.216	0.213	0.142	0.125	0.397
Panel B: Differential impact (lagged credit dummy for each source)						
Bank credit	0.170	0.009	0.034	0.019	-2.036	0.560
	(0.173)	(0.362)	(0.108)	(0.054)	(3.280)	(14.708)
MFI credit	-0.187	-0.458	-0.038	0.024	5.560	16.310
	(0.163)	(0.284)	(0.065)	(0.046)	(5.039)	(18.307)
Informal credit	-0.342**	-0.081	-0.037	0.006	-0.310	-25.343**
	(0.137)	(0.254)	(0.056)	(0.039)	(3.582)	(10.311)
Observations	1,582	1,582	1,582	1,582	509	353
R-squared	0.323	0.218	0.212	0.140	0.134	0.504

Note: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at household levels. (***P<0.01, **P<0.05, *P<0.1). Third lag of credit access is used to see longer term impact.

Annex Table 7: Credit Impact on Welfare Indicators Using Fourth Credit Lag

	Rented in land	Total rice yield	Income	Poverty	School enrolment rate Girls	Boys
Panel A. Access to any credit (lagged credit)						
Any credit	0.108	-0.107	-0.004	-0.028	-1.537	2.596
	(0.124)	(0.243)	(0.058)	(0.034)	(1.722)	(3.082)
Observations	791	791	791	791	262	155
R-squared	0.409	0.257	0.382	0.154	0.118	0.105
Panel B: Differential impact (lagged credit dummy for each source)						
Bank credit	-0.173	-0.024	-0.126	-0.026	1.758	3.644
	(0.208)	(0.407)	(0.097)	(0.057)	(3.129)	(4.972)
MFI credit	-0.163	0.842	0.089	-0.066	-7.189*	3.067
	(0.309)	(0.606)	(0.145)	(0.085)	(3.973)	(8.396)
Informal credit	0.221*	-0.252	0.041	-0.009	-0.600	1.761
	(0.134)	(0.263)	(0.063)	(0.037)	(1.840)	(3.391)
Observations	791	791	791	791	262	155
R-squared	0.411	0.260	0.384	0.154	0.128	0.108

Note: Household and village characteristics are used as control variables in all regressions. (***P<0.01, **P<0.05, *P<0.1). Fourth lag of credit access is used to see impact after 25 years using cross sectional analysis.