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

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Using 791 consistent households in the balanced panel, comprising 3,985 households in the unbalanced panel—from a nationally representative, multipurpose, five-round (1988, 2000, 2004, 2008, and 2014) Mahabub Hossain Panel Data in Bangladesh—we provide evidence for the long-term impact of different rural credit sources—which include formal banks, quasi-formal microfinance institutes, and informal channels—on household welfare indicators. We find that the long-term impact of access to rural credit on a few welfare indicators is statistically insignificant and sometimes negative. This finding mostly holds when we investigate the impact of different rural credit sources separately. Our results raise a question on the progressive lending of some credit sources, especially microfinance institutes, and have implications for the introduction of nationwide credit bureaus in Bangladesh.

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I. 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 or improve their welfare (González 2014, Lin et al. 2019, Maîtrot and Niño-Zarazúa 2017). Rural households in Bangladesh 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 quasi-formal sources of credit. Friends, relatives, and local moneylenders constitute informal credit facilities. The existing theory of changes, mostly developed based on the microfinance literature and applicable to formal banks and informal credit sources (Maîtrot and Niño-Zarazúa 2017, J-PAL 2018, Lin et al. 2019), has several channels: (i) credit enhances household investment in business activities, which improves household business entrepreneurship and economic outcomes; (ii) credit helps households mitigate the impact of shocks through consumption smoothing or insurance; and (iii) credit also achieves some noneconomic outcomes such as human capital and child education, socio-psychological (health), empowerment, and life satisfaction. In Bangladesh, formal banking services are yet to cover most rural households due to high operating costs and less opportunity for profit (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 met to a certain extent. However, individual moneylenders and other informal credit sources continue to play a role in rural areas, even with higher interest rates, due to their convenient accessibility (Manig 1996, Mallick 2012, Hossain and Bayes 2018). Meanwhile, microcredit, a great innovation for easing credit access for the poor and offering a pathway out of poverty, has become a debatable topic in recent years because of its differential impact on various welfare outcomes (Banerjee et al. 2015; Banerjee, Karlan, and Zinman 2015).[1]

Rural credit, especially microcredit, has been established as successful in many parts of the world. Many researchers and scholars have examined the causal effect

[1] We use the terms "microcredit" and "microfinance" interchangeably.

of microcredit on rural households' welfare indicators. However, informal credit and other non-MFI credit sources have been largely unexplored. Thus far, recent evidence based on randomized control trials has provided rather weak evidence of the impact of microcredit on household income (Karlan and Zinman 2011; Augsburg et al. 2012; Desai, Johnson, and Tarozzi 2013; Angelucci, Karlan, and Zinman 2015; Banerjee et al. 2015; Hossain et al. 2019). Some observational studies have found significant effects on borrowers' solvency and poverty measures (Khandker 1998, 2005; Zaman 1999; Tedeschi 2008; Rui and Xi 2010; Imai and Azam 2012; Khandker and Samad 2014) while others (Diagne and Zeller 2001, Shaw 2004) fail to document 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 microcredit impact evaluations has been suggested by numerous researchers (LaLonde 1986; Khandker 2005; Kabeer 2005; Islam 2011; Banerjee et al. 2015; Banerjee, Karlan, and Zinman 2015). Most previous microfinance studies were unable to control for fungibility (Pitt and Khandker 1998, Hulme 2000, Khalily 2004), which may have overestimated the results. The failure to consider other close substitutes for MFIs, such as formal banks and informal credit, has been regarded as one of the challenges in evaluating microcredit programs (Banerjee 2013, Banerjee et al. 2015). Owing to the lack of longer-term household-level panel data, there is limited evidence on whether rural credit access has a sustainable welfare impact. In addition to contributing to the continuing debate on the welfare impact of microcredit, we evaluate the impact of different credit sources on household welfare from a long-term perspective covering 3 decades.

Against this backdrop, we employ a widely used and nationally representative, multipurpose, five-round (1988, 2000, 2004, 2008, and 2014) Mahabub Hossain Panel Data (MHPD) with a 25-year time span to estimate the long-term impact of different credit sources in rural Bangladesh.[2] Our study provides somewhat similar, albeit somewhat contradictory, evidence of previously documented (weak) evidence of the long-term impact of microcredit benefits with a 20-year time span (1991–2011) using another comparable data set (Khandker and Samad 2014). Our study also provides

[2] This data set, referred to as the MHPD by the World Bank (Gautam and Faruqee 2016), has been widely used to investigate different aspects of rural and agricultural transformation, including the impact of some policy interventions, but is seldom used to see the long-term impact of rural credit that this study is aimed at. An extensive review of the studies that used the MHPD is included in Malek et al. (2022), which documented more than 70 academic studies, including recent papers by Nargis and Hossain (2006); Hossain (2007); Hossain, Rahman, and Estudillo (2009); Balagtasa et al. (2014); Kikkawa, Matsumoto, and Otsuka (2018); Kikkawa and Otsuka (2020); and Mahmud, Sawada, and Tanaka (2022).

evidence of the long-term impact of formal bank sources and informal channels, which is completely new in the recent literature.

In this study, to address the key identification challenges arising from voluntary participation in rural credit sources, we use a household-level, panel fixed effects model to estimate the impacts on different outcome indicators. Our results suggest that access to rural credit from any source has some positive contemporary (short-term) impacts and some negative long-term impacts, though not statistically significant, on a few household welfare indicators. Furthermore, when different credit sources are considered, we find that (i) bank credit has no statistically significant long-term effect on household welfare; (ii) MFIs have a negative long-term impact on household welfare indicators such as rented-in land and rice production, while their impact on other welfare indicators—such as household income, poverty status, and children's school enrollment—is not statistically significant; and (iii) the long-term impact of informal credit sources is negative for rented land and households but not significant for other welfare indicators. Our results raise a question about the effectiveness of progressive lending from some credit sources, especially MFIs. Thus, our results have implications for the introduction of nationwide credit bureaus or community information pools as suggested by, for example, Mobarak and Dimble (2019); and Mahmud, Sawada, and Tanaka (2022). We also recommend that facilitating credit access without other constraints to create entrepreneurship may not be enough to increase investment and profits accrued from credit investment by rural households.

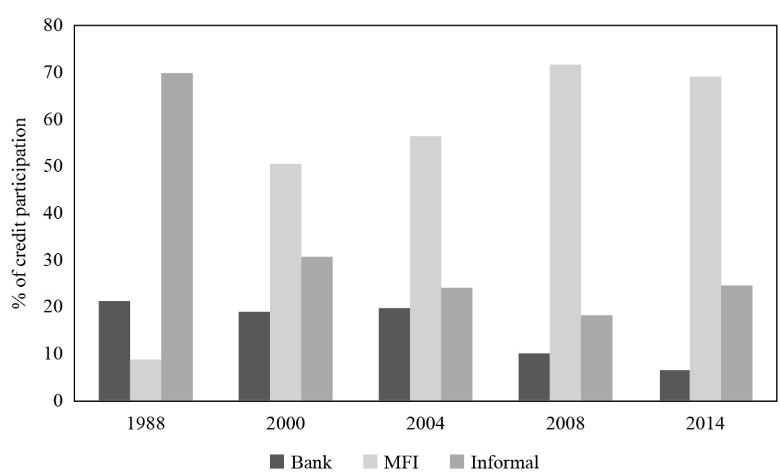
The remainder of this paper is organized as follows. Section II provides an overview of the rural credit market in Bangladesh. Section III describes the data set Section IV discusses empirical strategies. Section V presents our main empirical results together with a set of robustness checks. A discussion of the not significant and/or negative long-term impact of rural credit is also presented. The final section concludes the study and discusses future research directions.

II. Overview of the Rural Credit Market in Bangladesh

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

At present, 60 scheduled banks, five nonscheduled banks, and 34 nonbank financial institutions operate throughout Bangladesh (Bangladesh Bank 2021). According to the central bank, the number of rural bank branches should comprise at least 50% of the total number of new branches approved in a given calendar year. Currently, the total number of bank branches is 10,588, of which 5,452 are located in urban areas and 5,136 are located in rural areas. Only 10.3% of formal banking loans and advances have been disbursed through urban branches (Bangladesh Bank 2021). 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 shown in Figure A1 of the Appendix. Loans and advances in urban branches have expanded at an increasing rate since 2000, with a sudden surge in 2011 due to increased government borrowing from the banking sector, while total credit disbursements by rural branches have observed slow growth. The lack of loan demand, high operating costs per loan, and relatively small deposits make rural branches less profitable while also incurring higher borrowing costs, which induces banks to concentrate only on urban areas (Armendáriz and Morduch 2007). According to Figure 1, borrowing from commercial banks indicates a declining trend from 1988 to 2014, whereas MFI borrowing demonstrates an increasing trend over the same period.

Figure 1. **Trend of Credit Participation by Rural Households from Different Sources**



MFI = microfinance institution.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

In 1959, Akhter Hameed Khan, a social scientist, initiated the "Comilla Model" for rural advancement, which failed due to inefficient control and lack of donor funding (Berg, Emran, and Shilpi 2013). The founder of Grameen Bank, Muhammad Yunus, and the late Fazle Hasan Abed of BRAC, the largest nongovernmental organization that originated in Bangladesh, learned some lessons from this failure. 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 in 2006, together with its founder, for contributions to social development and the rural economy. Following the approach and success of Grameen Bank and BRAC, many other MFIs have evolved over the years, and they are associated with diversified social programs to connect to the poor in rural areas. According to the Microcredit Regulatory Authority, Bangladesh has more than 30 million borrowers of microcredit, which is the most in the world after India. A total of 783 registered MFIs with 17,120 branches operate mostly in rural areas. According to Figure A2 of the Appendix, total microcredit disbursement through 2017 by MFIs (including Grameen Bank), government projects, commercial banks, and other microlenders registered with the Microcredit Regulatory Authority was Tk1,313.67 billion. Approximately 91% of borrowers in the microfinance sector in Bangladesh are women, and 40% of all loans are provided for agricultural purposes.

Previously, the urgent credit requirements of rural households were mainly served by *mohajons* (moneylenders) and landowners due to the lack of formal sources of credit. These moneylenders, also called "usurious monopolists," charged exorbitant rates of interest for lending money. The lack of required collateral for formal credit and the convenient accessibility of informal credit resulted in the latter being sustainable over decades despite charging interest rates of 100%–120% per annum (Berg, Emran, and Shilpi 2013). This form of borrowing mostly occurs without legal paperwork, is sometimes inaccurate, and may have a fraudulent intention, leading to people taking on excessive financial commitments that can drive them into acute poverty (Mudahar and Ahmed 2010). Our estimation suggests that the share of informal credit has declined over the years in rural areas with an increase in microfinance program coverage and the spread of loans (Figure 1).

III. Sampling Design, Data Description, and Summary Statistics

As mentioned earlier, we used five rounds of the MHPD (1988, 2000, 2004, 2008, and 2014). The data were collected by the Bangladesh Institute of Development, International Rice Research Institute, and BRAC. The first-round survey was conducted during 1987–1988 as a component of the Livelihood Systems in Bangladesh project. Detailed information on farm and nonfarm activities, borrowing, income and expenditure, poverty, resource ownership, and other household- and village-level characteristics was collected.

It is a panel-structured survey covering 62 of the 64 districts (in total) in the country. The sample villages and households were selected based on a multistage random sampling method using the socioeconomic indicators of each district (Rahman and Hossain 1995; Hossain, Rahman, and Estudillo 2009). During the census period, due to administrative problems, two villages were dropped. On average, data from 153 households from each of the remaining villages were collected. Based on the land tenure and ownership of all households in the villages, households were classified into four groups (rich, solvent, poor, and ultra-poor) for stratification, following the participatory rural appraisal approach. From each of the 64 villages, 20 households were randomly selected in the first MHPD round of 1997–1988, resulting in a total of 1,280 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 divide into multiple new households (e.g., through marriage) and some permanently migrated. To address sample attrition and keep the sample representative of the population, new households were added in each round. In 2000, a second-round survey was conducted with 1,880 households. The third-round survey was conducted in 2004 with 1,930 households, and in the fourth round, the sample comprised 2,010 households. In the final round of the survey in 2014, the total sample size was 2,846, including households present in the first four rounds and their offshoots.

To conduct panel-data analysis, we first created a balanced panel data set of 804 households. We determined that some households had moved to and from other villages. To control for this in the second stage, we dropped those households and were left with 791 households that are present in all five rounds of the survey. To summarize the statistics, we used only those 791 consistent households, as shown in Table 1. A histogram of the repeated households in the study villages for all five rounds is shown in Figure A3 of the Appendix.

Table 1 indicates that, over the study period, household size, the share of households headed by a male, the amount of land owned by households, the percentage of working members in a household, and farm size all decreased. By contrast, household heads' age and education level, household migration, and access to electricity all increased gradually from 1988 to 2014. This represents rural development, in terms of education, migration, life expectancy, and access to electricity. Due to the scarcity of land and the nature of the law, land ownership declines with an increasing number

Table 1. **Characteristics of Sample Households**

Variable	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	49.30	48.10
	(13.96)	(12.41)	(12.75)	(13.70)	(13.50)
Education of head (years of schooling)	3.17	3.76	3.98	3.95	4.55
	(3.94)	(4.21)	(4.41)	(4.29)	(4.43)
Highest level of education by a member of the household	4.83	6.89	7.23	7.62	8.89
	(4.27)	(3.92)	(3.90)	(3.67)	(4.41)
Share of working members in the household	0.30	0.30	0.34	0.34	0.31
	(0.15)	(0.16)	(0.18)	(0.17)	(0.16)
Land owned by household (hectares)	0.70	0.58	0.52	0.50	0.40
	(1.04)	(1.02)	(0.87)	(0.88)	(0.73)
Migration (if any member migrated = 1)	0.10	0.50	0.21	0.25	0.35
	(0.30)	(1.11)	(0.41)	(0.43)	(0.47)
Distance to *upazila* (subdistrict) headquarters from village (km)	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)
Number of borrowers	279	314	340	367	401
Number of nonborrowers	512	477	451	424	390

km = kilometer.
Note: The numbers in parentheses are standard deviations.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

of households. Only 35% of households reported borrowing from either banks, MFIs, or informal sources in the first-round survey; this share increased to 51% in 2014.

Table 2 lists the main outcome variables of household welfare. In rural areas, households with a labor force and bullocks for cultivation try to access more land to cultivate crops. They can take the land as rented-in from others. Households' rented-in land increased from 1988 (0.13 hectares) to 2014 (0.16 hectares), while the total amount of land owned by households declined from 0.70 hectares to 0.40 hectares over the survey period (Table 1). Thus, although land ownership decreased, rented-in land slightly increased. Because of the application of green revolution technologies in Bangladesh, agricultural productivity has increased exponentially in recent decades, and modern rice variety adoption continues to replace traditional varieties. In 1988, 47% of the total rice production (780 kilograms per household) used traditional varieties, whereas 93% of the rice production (1,652 kilograms per household) adopted the modern variety in 2014.

Table 2. **Summary of Main Outcome Variables**

Variable	1988	2000	2004	2008	2014
Rented-in land (hectares)	0.13	0.13	0.15	0.12	0.16
	(0.33)	(0.33)	(0.33)	(0.30)	(0.44)
Total rice production (kg)	1,657	2,065	1,732	1,544	1,652
	(3,316)	(5,943)	(3,017)	(2,829)	(2,873)
Total household income (Tk/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)
Noncrop 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, nonpoor = 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	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	56.52	91.96	94.86	96.15	98.09
	(47.36)	(26.06)	(21.45)	(18.46)	(13.70)

kg = kilogram, Tk = taka.
Notes: Numbers in parentheses are standard deviations. All monetary figures are adjusted for inflation using a consumer price index of 28.66, 53.91, 64.60, 87.73, and 136.13 for 1988, 2000, 2004, 2008, and 2014, respectively (base year = 2010).
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Household income, which is the main indicator of welfare, was reported for each of the five MHPD rounds. Here, all monetary figures are adjusted based on the consumer price index (base year 2010), which is obtained from International Monetary Fund statistics. Household total income increased from the first-round survey through 2014, rising to Tk147,821 from Tk120,428 in 1988, with slight decreases observed in 2000 and 2004. Consumer price index-adjusted income amounts fell 2% from 1988 to 2000 and 5% from 2000 to 2004. Total income per household increased 13% from 2004 to 2008 and 16% from 2008 to 2014. Household income from crop cultivation, total agricultural income, and wage income all showed downward trends, while business income and remittance inflows increased over the review period.

From 1988 to 2014, rural poverty declined by almost half. A poverty status indicator is calculated using the absolute poverty line income as per the Food and Agriculture Organization of the United Nations (FAO) norm (Table A1 of the Appendix). Households that are unable to afford the minimum required food (2,110 calories of food per head) and nonfood expenses (estimated using the 30%–70% ratio for food versus nonfood expenses) are treated as "absolute poor." Otherwise, the household is treated as "nonpoor."

School enrollment for an eligible child (more than 5 years old) is a mandatory pre-requirement to develop an educated society.[3] In rural areas, where acute poverty prevails, households find it difficult to send their children to school because of financial difficulties and a lack of awareness of the positive impacts of education. Of the total number of boys and girls, whether in a village or the country as a whole, the percentage of students attending school is the rate of enrollment for each gender. The school enrollment rate in Bangladesh for boys increased from 64.5% to 96.8% from 1988 to 2014. In 1988, girls' school enrollment rate was 56.5%, which was less than that of boys (64.5%); however, this trend had reversed by 2014, with girls' school enrollment rate reaching 98.1%, surpassing that of boys (96.8%).

IV. Empirical Strategies

To measure the welfare effect, we compare the outcomes of credit takers and noncredit takers. However, a simple comparison is questionable due to the nonrandom nature of credit disbursement, self-selection bias, fungibility, and other unobservable factors that affect credit participation and household welfare (Pitt and Khandker 1996, 1998; Khandker and Faruqee 1999; Bao and Izumida 2002; Khalily 2004; Khandker 2005; Quach, Mullineux, and Murinde 2005; Islam 2011; Khandker and Samad 2014). The household credit participation decision is highly influenced by its members' capacity to repay, entrepreneurship skills, latent abilities, and other unobserved behaviors. To address these issues, we use a household-level fixed effects 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:

$$W_{it} = \gamma_0 + \beta_k C_{i(t-k)} + \gamma_1' X_{it} + \delta_t + \alpha_i + \varepsilon_{it}, \qquad (1)$$

[3] Enrollment rate = (number of children attending school/total number of kids in household) × 100. To calculate enrollment variables, only school enrollment rates for children aged 6–10 years are considered.

where W_{it} represents welfare indicators (e.g., household income) for household i at time t. The intervention variable $C_{i(t-k)}$ indicates household i's access to credit from any source in the current period if $k = 0$, in the previous period if $k = 1$, or two periods prior if $k = 2$. The covariates are denoted by vector X_{it}, which includes the following household- and village-level observed characteristics: total land owned by a household (hectares), age of household head, age squared, gender of the household head, education level of the household head (schooling years), education squared, highest education attainment from household (schooling years), household size (number of members), the percentage of working members in the household, migration status, and access to electricity. δ_t and α_i denote the time and household fixed effects, respectively. ε_{it} is an idiosyncratic error term. The coefficients of interest are β_k for $k = 0$, 1, and 2, which measure the effect of credit access (in the current or previous periods) on the outcome variable. Specifically, β_0 measures the contemporary (or short-term) effect of credit access on household welfare, whereas β_1 and β_2 capture the long-term effect of past credit access on the current outcome.

We then conduct a more detailed analysis of the effects of the different credit sources. To do so, we replace $C_{i(t-k)}$ in equation (1) with indicators for three different credit sources: bank credit, MFI credit, and informal credit:

$$W_{it} = \gamma_0 + \beta_{Bk}\,\mathrm{Bank}_{i(t-k)} + \beta_{Mk}\,\mathrm{MFI}_{i(t-k)} + \beta_{Ik}\,\mathrm{Inf}_{i(t-k)} + \gamma_2' X_{it} + \delta_t + \alpha_i + \varepsilon_{it}, \quad (2)$$

where $\mathrm{Bank}_{i(t-k)}$, $\mathrm{MFI}_{i(t-k)}$, and $\mathrm{Inf}_{i(t-k)}$ indicate household i's access to the credit provided by banks, MFIs, and informal channels, respectively, in the current and past periods. The coefficients β_{Bk}, β_{Mk}, and β_{Ik}—with $k = 0$, 1, and 2—capture the short- and long-term effects of each credit source on the household's outcome. The estimates of regression equations (1) and (2) for different outcome variables are presented in Tables 3–7. The outcome variables we consider include rented-in land, rice production, household income and its components, poverty reduction, and children's school enrollment. In each table, panel A reports the estimates of β_k in model (1), and panel B presents the estimates of β_{Bk}, β_{Mk}, and β_{Ik} in model (2). Columns (1), (2), and (3) correspond to $k = 0$, 1, and 2, respectively. The numbers in parentheses are robust standard errors clustered at the household level.

As we use observational data, the key identification challenge is to address the selection bias that arises from voluntary participation in microcredit. In this study, we employ a fixed effects model to deal with the selection of unobservable variables and include household- and village-level characteristics (i.e., regression adjustment) as covariates to address the selection of observables. Specifically, using balanced panel data, our fixed effects model includes time and household fixed effects, which eliminate the bias due to the time trend that impacts all households, as well as the bias due to time-invariant unobserved household characteristics (Wooldridge 2010, Hsiao 2014). In addition, including the covariates X_{it} in models (1) and (2) adjust for the differences in household characteristics such as total land owned, age, education, family size, and access to electricity. Table A2 of the Appendix checks the balance of covariate X in the initial period (1988). This shows that the normalized differences between the treated and control groups are small for all covariates, which confirms the similarity of the covariate distribution by treatment status. Therefore, our regression adjustment adequately removes most of the selection bias associated with the differences in these covariates (Imbens and Rubin 2015).

The fixed effects model, which is also known as the difference-in-differences (DD) model, has been widely used to study microfinance impacts.[4] In a comprehensive literature review, Maîtrot and Niño-Zarazúa (2017) surveyed 50 papers on microfinance impacts in developing countries from 1990 to 2015, among which 12 employed fixed effects or DD as the main empirical method (see Table A1 of the Appendix).[5] Let us make more detailed comparisons between our fixed effects model and some important studies that also used the fixed effects or DD method. Our fixed effects model is similar to those used by Khandker and Samad (2014), Imai and Azam (2012), and DeLoach and Lamanna (2011), all of which include household and/or time fixed effects.[6] Berhane and Gardebroek (2011) used a fixed effects model that included household fixed effects and an individual-specific linear trend. Our fixed effects model accounts for the household-specific effect in the same way as theirs, whereas our modeling of the time-specific effect is slightly different. Simply speaking, they allow for the time trend to differ among households but maintain the assumption of the linearity of the time trend. In contrast, we do not restrict the form of the time-specific effect but assume it equally impacts all households. Islam (2011) used both the DD and difference-in-difference-indifferences (DDD) methods. His DD method is equivalent to including time and program village fixed effects. In comparison, our model includes time and household fixed effects, which control the (time-invariant) unobserved individual characteristics at a less aggregate level. The DDD method of Islam (2011) introduced another dimension, eligibility, which is equivalent to additionally including the second-order interacted fixed effects between any two of

[4]A DD model can be viewed as a fixed effects with the fixed effects usually imposed at an aggregate level—for example, the village level if the treated villages have the microcredit program while the control villages do not.

[5]Since fixed effects and DD models require data from multiple periods, not every study is able to apply it.

[6]As the main outcome variable in DeLoach and Lamanna (2011) is the height of the child, they include another child-specific fixed effect.

the three fixed effects: time, program village, and household eligibility. Therefore, the DDD method of Islam (2011) included more fixed effects (six) than ours (two), but none of his six effects is as refined as our household level. Khandker and Samad (2014) applied the household fixed effects model to three-period panel data (survey years 1991–1992, 1998–1999, and 2010–2011) from Bangladesh to study the dynamic effect of microcredit. Their intervention variables are the year-specific (or cumulative) loan amounts of a household borrowed by male and female members, separately. By adding a lagged loan amount to the model specification, the model captures the effect of past credit on current outcome variables. Recall that our intervention variables are the current and past credit access dummies, which play a comparable role in measuring short- and long-term effects.

Some studies, such as Imai and Azam (2012), and Islam (2011), combined propensity score matching with the fixed effects or DD model. In general, matching is a more robust method to address the selection of observables, especially when the distributions of the covariates differ substantially between the treated and control groups. However, as shown in Table A2 of the Appendix, the distributions of the covariates in our data were similar between the treated and control groups. Therefore, the use of regression adjustment or propensity score matching does not matter much when estimating the causal effect (Imbens and Rubin 2015).

V. Regression Results and Discussion

A. Main Results

1. Impact on Rented-In Land

Rural credit-constrained households are likely to ease liquidity problems through formal or informal borrowing. Therefore, credit access can encourage rural households to engage in more farm activities. In rural areas, landless and land-poor households require financial capital to obtain cultivable land, as rented-in land from land-resourced farm households or from absentee landlords, to maintain farming livelihoods and ensure food security. Farmers usually pay a fixed rent before growing crops on rented-in 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 rented-in land by about 23.3% compared to nonborrowers. Column (1) of panel (B) further shows that only credit from formal banks, which increases rented-in land by 61.8%, is the main catalyst. This is probably because the agricultural loan sizes of commercial banks, Bangladesh Krishi Bank, and Rajshahi

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) First Credit Lag**	**(3) Second Credit Lag**
Panel A: Credit participation dummy from any source (1 = yes, 0 = no)			
Any credit	0.233**	–0.208**	–0.086
	(0.099)	(0.099)	(0.092)
R-squared	0.045	0.044	0.042
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.618***	–0.023	–0.165
	(0.216)	(0.188)	(0.158)
MFI credit	0.117	–0.132	–0.248*
	(0.116)	(0.121)	(0.129)
Informal credit	0.269	–0.398***	0.174*
	(0.140)	(0.139)	(0.116)
R-squared	0.050	0.047	0.046

MFI = microfinance institution.
Notes: Household and village characteristics—such as age of household head, age squared, education level of household head, education squared, gender of household head, land owned, household size, farm size, total household workers, migration status, and electricity access—are controlled for. The results were estimated using panel data from 791 households. Year and household fixed effects are applied to both panels. Robust standard errors in parentheses are clustered at the household level. *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Krishi Unnoyan Bank are usually higher than those from MFIs and informal sources. As a result, credit from sources other than banks may not be sufficient for households to rent more cultivable land.

We find an insignificant positive short-term (current year) impact of MFI credit (column 1) on rented-in land, consistent with the large-scale randomized evaluation of the microcredit program for tenant farmers (Hossain et al. 2019). 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 MFI credit has an insignificant negative impact, but two-period-lagged MFI credit has a significant negative impact, with rented-in land reduced by 24.8%. In the case of informal credit, one-period-lagged credit has a significant negative impact, reducing rented-in land by 39.8%, and two-period-lagged informal credit has some positive impact, which is somewhat inconsistent.

2. Impact on Rice Production

Approximately 67% of the total cultivated area in Bangladesh is used for rice production (Hossain et al. 2019), accounting for 75% of total crop production value

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

Main Dependent Variable: Log of Total Rice Production	(1) Current Credit	(2) First Credit Lag	(3) Second Credit Lag
Panel A: Credit participation dummy from any source (1 = yes, 0 = no)			
Any credit	0.155	–0.233	–0.00
	(0.150)	(0.154)	(0.148)
R-squared	0.074	0.075	0.073
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.687**	–0.224	–0.204
	(0.271)	(0.320)	(0.258)
MFI credit	0.225	–0.165	–0.292*
	(0.182)	(0.188)	(0.218)
Informal credit	–0.000	–0.276	0.243
	(0.208)	(0.211)	(0.178)
R-squared	0.077	0.075	0.076

MFI = microfinance institution.

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

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

(Talukder and Chile 2014), the production cost of which is often mobilized from the rural credit market. Therefore, we use total household rice production (hereafter, rice production) to show the impact of rural credit. The impact of current and lagged credit on rice production per household is estimated.

Table 4 summarizes the effects of current (latest) and previous credit access on rice production, controlling for household and village characteristics as well as the fixed effects. Access to credit does not have any significant impact on rice production, not only in the latest period, but also in earlier periods.

If credit access is disaggregated into three main sources, then it is established that the significant positive impact of current credit participation on rice production is associated only with bank credit. Bank credit increased rice production by 68.7%. This result is consistent with Miah, Alam, and Rahman (2006), who studied Rajshahi Krishi Unnoyan Bank and Grameen Bank loans and noted that farmers use bank loans more than microcredit for rice production and that rice production increased significantly compared to nonborrowers. The short-term positive impact of different credit sources on rice production is consistent with the existing literature, including randomized evaluations (Bao and Izumida 2002; Isham 2002; Binam et al. 2003; Croppenstedt, Demeke, and Meschi 2003; Abdulai and Huffman 2005; Javed et al. 2006; Rahman 2011; Islam, Sumelius, and Bäckman 2012; Girabi and Mwakaje 2013; González 2014; Anang, Bäckman, and Sipiläinen 2016; Abate et al. 2016; Chandio et al. 2018; Hossain et al. 2019). Such literature shows that farmers utilize credit to adopt modern technology, high-yield variety seeds, improved fertilizers, and other inputs, which increases technical efficiency and productivity, and, hence, rice production.

However, in the longer term (using first and second credit lags), the bank credit impact is not sustained and no other credit source increases rice production in the longer term. Instead, we find a negative impact of MFI credit on rice production when we use the second credit lag.

3. Impact on Household Income

Most rural household income sources are not restricted to one income source but rather have multiple income sources, which helps them to smoothly run consumption and address shocks. The major components of household income are crop, noncrop farm, wage, business, and remittance income. Therefore, any individual measurement of an income component is likely to lack accuracy; therefore, it is optimal to consider

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) First Credit Lag**	**(3) Second Credit Lag**
Panel A: Credit participation dummy from any source (1 = yes, 0 = no)			
Any credit	0.041	0.031	–0.037
	(0.034)	(0.032)	(0.034)
R-squared	0.201	0.201	0.201
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	0.047	0.035	0.033
	(0.065)	(0.057)	(0.064)
MFI credit	0.061	0.053	–0.051
	(0.038)	(0.039)	(0.042)
Informal credit	–0.017	0.011	–0.065*
	(0.050)	(0.049)	(0.040)
R-squared	0.202	0.201	0.202

MFI = microfinance institution.

Notes: Household and village characteristics—such as age of household head, age squared, education level of household head, education squared, gender of household head, land owned, household size, farm size, total household workers, migration status, and electricity access—are controlled for. The results were estimated using panel data from 791 households. Year and household fixed effects are applied to both panels. Robust standard errors are clustered at the household level and are presented in parentheses. * = $p < 0.1$.

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

all related income sources. We show the regression results for total household income and the different components of household income in Table A3 of the Appendix.

Using fixed effect models (1) and (2), we note consistent results with the previous studies, where most experimental studies and other nonexperimental studies failed to document any significant positive impact on total household income. Access to credit, for either the current year or lagged credit, does not increase household income. When the credit impact is segregated into bank, MFI, and informal credit, we also did not establish any evidence that proves that access to any credit source has a positive impact on household income. Rather, we find a significant negative impact of informal credit on household income when we use the second credit lag.

Regression results on different components of household income, as presented in Appendix Table A3, show that current-year access to any credit source increases income from crops and businesses but reduces remittance earnings for borrowers when compared to nonborrowers. The negative impact of current-year access to remittance income is not surprising because remittance workers need to pay a large amount of their initial earnings to cover their living arrangements and other expenses, which makes them initially remit a lesser amount to their household in their home country. Rather, households need to pay interest on the credit used to send remittance workers abroad before they migrated. However, the existing literature does not document such phenomenon, rather it documents the impact of remittances on credit.

Differential impact estimates suggest that bank and informal credit do not have an impact on any of the components of household income, whereas MFI credit alone increases agricultural (crop and noncrop farm) income and business income. Such differential impact estimates may indicate that microcredit is the main underlying reason for the rise in agriculture and business income in the short term. Surprisingly, these impact estimates are inconsistent and become negative in the long term when we use the second credit lag. This means that, although MFI credit can initially be helpful in agriculture and business, the impact is not sustained for a longer period. On the other hand, wage income for households that access bank credit increases significantly (in the case of using a second credit lag) and remittance income for households that access informal credit increases slightly (in the case of using a second credit lag).

4. Impact on Poverty Reduction

Access to credit facilities for rural, credit-constrained households improves productivity, smoothens income and consumption flows, diversifies other income-earning options, generates self-employment, and increases other benefits (Khandker 1998, Pitt and Khandker 1998, Robinson 2001, Morduch 2011). As defined earlier,

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

Main Dependent Variable: Household's Poverty Status	**(1) Current Credit**	**(2) First Credit Lag**	**(3) Second Credit Lag**
Panel A: Credit participation dummy from any source (1 = yes, 0 = no)			
Any credit	–0.031	–0.019	0.020
	(0.024)	(0.023)	(0.022)
R-squared	0.107	0.106	0.106
Panel B: Differential impact (credit dummy for each credit source)			
Bank credit	–0.020	–0.014	–0.001
	(0.047)	(0.04)	(0.039)
MFI credit	–0.009	–0.034	0.009
	(0.028)	(0.029)	(0.030)
Informal credit	–0.044	0.009	0.042
	(0.034)	(0.033)	(0.028)
R-squared	0.107	0.107	0.107

MFI = microfinance institution.
Notes: Household and village characteristics—such as age of household head, age squared, education level of household head, education squared, gender of household head, land owned, household size, farm size, total household workers, migration status, and electricity access—are controlled for. The results were estimated using panel data from 791 households. Year and household fixed effects are applied to both panels. Robust standard errors are clustered at the household level and are presented in parentheses.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

poverty estimates are correlated with household income and expenditure, which is the ultimate outcome of increasing household welfare. Table 6 shows the regression results for the impact of credit on poverty using household-level panel fixed effects.

During the survey period (1988–2014), the rural poverty incidence was reduced from 0.59 to 0.38, where being poor is given the value of 1 and being nonpoor is given the value of 0. Whether credit access played a role in reducing poverty during the study period needs to be analyzed. Column 1 of the fixed effects regression demonstrates that the current year's access to any type of credit reduces household poverty, albeit not significantly. In addition, credit from formal banks, MFIs, or informal sources (panel B) does not assist rural households in relieving poverty. Columns 2 and 3 present the long-term impact (first and second credit lag) estimates. 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. Our findings are consistent with the findings of nonexperimental studies, such as Diagne and Zeller (2001), and Shaw (2004), and also with previous experimental studies—such as Karlan and Zinman (2011); Augsburg et al. (2012); Angelucci, Karlan, and Zinman (2015); Attanasio et al. (2015); Banerjee et al. (2015); and Crépon et al. (2015)—on microfinance that did not document any positive impact on poverty reduction. However, using nonexperimental observational data, such as that of Khandker and Samad (2014), we found that extreme poverty was reduced by both past and current loans, suggesting that microcredit brings some people out of extreme poverty in the short term and additional people out of poverty in the long run, although their point estimates are negligible.

5. Impact on Children's School Enrollment

Children's school attendance is related to household income, distance to school, and other factors. Owing to government and nongovernment initiatives regarding compulsory primary education, there has been significant improvement in children's schooling outcomes for both boys and girls. In particular, the girls' education scenario changed substantially during the study period. Table 7 summarizes the results for both girls' and boys' school enrollment.

Current-year access to credit increases girls' school enrollment by approximately 5%, while boys' school enrollment decreased by about 4%, although the latter estimate was not statistically significant. Credit-taking for either agricultural needs or

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		First Credit Lag		Second Credit Lag	
	(1)	(2)	(3)	(4)	(5)	(6)
	Girls	Boys	Girls	Boys	Girls	Boys
Panel A: Credit participation dummy from any source (1 = yes, 0 = no)						
Any credit	4.979**	–4.191	–1.752	–1.791	–2.965	–1.510
	(2.456)	(4.539)	(2.363)	(4.644)	(2.063)	(3.717)
R-squared	0.085	0.053	0.074	0.050	0.077	0.049
Panel B: Differential impact (credit dummy for each credit source)						
Bank credit	10.126*	–4.457	–2.464	3.227	–3.366	0.478
	(5.363)	(5.986)	(2.061)	(4.997)	(4.244)	(3.487)
MFI credit	3.401	–4.693	–1.063	–1.874	–3.196	–6.989
	(3.188)	(5.764)	(3.211)	(6.20)	(3.269)	(4.642)
Informal credit	5.619	–0.784	–2.842	–3.567	–1.398	0.363
	(3.462)	(6.202)	(3.040)	(7.224)	(1.966)	(5.294)
R-squared	0.092	0.054	0.075	0.052	0.077	0.056

MFI = microfinance institution.

Notes: Household and village characteristics—such as age of household head, age squared, education level of household head, education squared, gender of household head, land owned, household size, farm size, total household workers, migration status, and electricity access—are controlled for. The results were estimated using panel data from 791 households. Year and household-fixed effects are applied to both panels. Robust standard errors are clustered at the household level and are presented in parentheses. ** = $p < 0.05$, * = $p < 0.1$.

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

business investment might have influenced rural households to engage more of their male children in income-generating activities. As access to credit does not increase agricultural production and household income, or improve a household's poverty status, households seem to invest less in children's education. In Bangladesh, girls' education is completely free up to higher secondary school levels with some financial benefits; therefore, credit-taking households send their female children, as there is less opportunity cost in sending them to school. After the first and second rounds 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 (Table 7, panel B) indicates that only current-year borrowing from formal banks increases girls' school enrollment rate (by about 10%), whereas MFI and other informal credit participation do not have an impact. The positive impact of different credit sources does not persist when lagged credit is used for children's school enrollment. This finding is consistent with several previous microfinance studies, such as Morduch (2011), and Banerjee et al. (2015), which did not establish any significant impact on similar schooling outcomes. However, Doan, Gibson, and Holmes (2014) indicated a causal relationship between formal microcredit and education expenditure by household in Viet Nam, and You and Annim (2014) found a positive impact of microcredit on children's schooling years. Khandker and Samad (2014) also found that in Bangladesh, school enrollment for boys and girls increased due to both past and current loans.

B. Robustness Check

In our main fixed effects model, we show that the impact of rural credit access on household welfare outcomes depends on both the current and the previous credit access. However, current-year credit participation from different sources may also be a significant cause that should be controlled to identify the disaggregated impact of lagged credit sources. Considering this issue, we control for current credit access, where time and household fixed effects are also applied. Using the first credit lag (Table A4 of the Appendix) and the second credit lag (Table A5 of the Appendix), we find no consistent results demonstrating the long-term impact of credit access on increasing household welfare. We find a negative impact on rented-in land and rice production when the first credit lag is used. However, this does not persist when we use the second credit lag. In addition, we used an unbalanced panel data set for all rounds (3,985 observations), with the same household-level, fixed effects estimation (Table A6 of the Appendix). The results suggest that the previous year's access (second credit lag) to any credit has no impact on any of the welfare indicators. In addition to the first and second credit lags, we use the third credit lag for long-term impact analysis. Using the third lag, in Table A7 of the Appendix, we see that the results are consistent with the previous analysis except for a reduction in rented-in land and boys' school enrollment rate by informal credit participation. These results are consistent with our main estimation. Therefore, we can conclude that in the long term, rural credit access does not contribute to the improved livelihoods of rural households by increasing income and reducing poverty, or by any other improvement in household welfare indicators.

C. Discussion: Why Is the Short-Term Positive Impact of Credit Not Sustained in the Long Term?

Our results suggest that access to rural credit from any source has some contemporary (short-term) positive impact, but no significant long-term positive impact, on increased household economic welfare. Rather, we find a negative long-term impact of access to MFIs for a few indicators—including rented-in land, rice production, and household income—and the same impact for informal credit sources on rented-in land and household income, which are not stable across the specifications. Our study provides somewhat similar, but also somewhat contradictory, evidence to that of Khandker and Samad (2014), who documented the limited positive long-term impact of MFI credit on two indicators: extreme poverty reduction and an increase in children's school enrollment. Thus, our results raise a question about the existing theory of changes that rural credit sources follow: Why is the positive contemporary (short-term) impact of credit access on household welfare outcomes not sustained in the long term?

To address this issue, we further investigate the effectiveness of progressive borrowing from different credit sources. We find that formal 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, this is known as progressive lending or dynamic incentive. Shapiro (2015) developed a model on the 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 five rounds of the MHPD (1988, 2000, 2004, 2008, and 2014), we estimated the dynamic incentives of MFI credit. Whether a household's previous year's access to

MFI credit has any significant impact on subsequent rounds of borrowing is estimated using cross-sectional data sets with the following set of equations for $t = 2, 3, 4, 5$:

$$C_{ijt} = \gamma_0 + \sum_{k=1}^{t-1} \beta_k C_{ij(t-k)} + \gamma_1' X_{ij} + \varepsilon_{it}, \tag{3}$$

where C_{ijt} indicates access to MFI credit (borrowers = 1 and nonborrowers = 0) for household i in village j in period t ($t = 5$ corresponds to the survey year 2014 and $t = 1$ corresponds to 1988). X_{ij} is the vector of covariates. The coefficient β_k measures the effect of Microfinance Institution credit access in the past period $t - k$ on current MFI credit-taking decisions. The empirical results are presented in Table 8, where each column corresponds to a value in t.

In 1988, only 9% of borrowing households participated in an MFI program, which is why first-round credit access did not provide an adequate rationale for the following round. However, households that participated in an MFI program in 2000 had a 29% higher likelihood than nonparticipants to receive credit from an MFI in 2004; this fell to 19% in 2008 and to 12% in 2014.

MFI credit access in 2004 and 2008 resulted in the same significant outcomes in subsequent rounds. This establishes the progressive lending concept that borrowers keep borrowing from the same sources and do not default because of their expectations to continue obtaining larger loans in the future.

However, such progressive lending does not clearly indicate that it is driven by entrepreneurial needs or the repayment of the previous loans. To this end, we present

Table 8. **Impact of Previous Microfinance Access on Next Round Microfinance Institution Credit Access**

Independent Variable	**2000**	**2004**	**2008**	**2014**
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)

MFI = microfinance institution.

Notes: Household and village characteristics are controlled for. The results were estimated using panel data from 791 households. Robust standard errors are clustered at the village level and are presented in parentheses. *** = $p < 0.01$, ** = $p < 0.05$.

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

recent evidence from a companion study (Mahmud, Sawada, and Tanaka 2022) that used the same MHPD and found that those who had borrowed for repayment of a previous loan at any time exhibited increased borrowing behavior on average in terms of the number of active loans, borrowing, multiple borrowing, multiple borrowing from MFIs, multiple borrowing from non-MFIs, and total amount of active loans from MFIs. They also found that such households had, on average, fewer assets and less income compared to most other households. In relation to their findings, our regression results find an insignificant or negative long-term impact of credit access on a few household welfare indicators, suggesting that the over-indebtedness problem among credit recipients could be an issue that might have prevented them from becoming sufficiently entrepreneurial and accruing significant benefits from credit investments. This explanation is consistent with that of Mobarak and Dimble (2019), who found that microcredit was able to alleviate a severe existing constraint and promote short-term welfare gains, in addition to funding small businesses.

VI. Conclusion

The rural credit market in Bangladesh has changed significantly since the central bank's directive that rural bank branches should comprise at least 50% of new branches approved in a given year. The role of microfinance innovation has also had a major effect, especially on the poor. We study the impact of various formal and informal credit sources, including credit accessibility, on different household welfare indicators. This study attempted to contribute to the ongoing debate on the impact of microcredit on different outcomes and estimate the long-term effect of rural credit access from different sources using a true panel data set. We used a five-round longitudinal survey over a period of 25 years (1988–2014). We applied a household-level, panel fixed-effects data set to examine the changes in household welfare indicators within households whose credit participation changes over time. Considering the concerns over the nonrandomized impact evaluation methodology, the methodology we followed is sufficiently sound. Our results suggest that access to rural credit from any source has some positive contemporary (short-term) impacts, but sometimes negative long-term impacts on a few household welfare indicators (albeit not statistically significant). This finding mostly holds when we investigate the impact of different rural credit sources separately. Our study provides somewhat similar but also contradictory evidence to that of Khandker and Samad (2014), who documented the limited positive long-term impact of MFI credit, over a 20-year period, on two indicators: extreme poverty reduction and an increase in children's school enrollment.

Thus, our results may raise a question about the existing theory of changes that rural credit sources follow: Why is the positive contemporary (short-term) impact of credit access on household welfare outcomes not sustained in the long term?

To address this issue, we further investigated the effectiveness of progressive borrowing from different credit sources and found that such a phenomenon applies to the case of microfinance borrowing. We also found an indication that progressive lending is not necessarily driven by entrepreneurial needs, but rather by the repayment of previous loans, suggesting the possible existence of an over-indebtedness problem among credit recipients, which might not prevent them from becoming sufficiently entrepreneurial and accruing significant benefits from credit investments in the long term. Thus, our results have implications for Bangladesh and other emerging economies with regard to the introduction of nationwide credit bureaus—as suggested by others such as Mahmud, Sawada, and Tanaka (2022)—and/or a community information pool, as suggested by Mobarak and Dimble (2019). We also recommend that facilitating credit access without addressing other constraints to entrepreneurship may not be enough to increase investment and the profits accrued by rural households from such credit investment.

To our knowledge, to date, there are two comparable studies that document the long-term impact of rural credit: ours and one conducted by Khandker and Samad (2014) on MFI credit. These two studies found both similar and contradictory evidence, especially on the positive impact of MFI credit, which provides a signal to conduct more research on the issue—specifically, on the greater potential effectiveness and long-term impact of rural credit sources, especially MFI credit, on several noneconomic indicators including borrowers' sociopsychology, empowerment, and life satisfaction. More research is also needed on entrepreneurship building among borrowers, the "bad selection" of borrowers, product innovation, and the digitalization of rural credit markets, among other topics.

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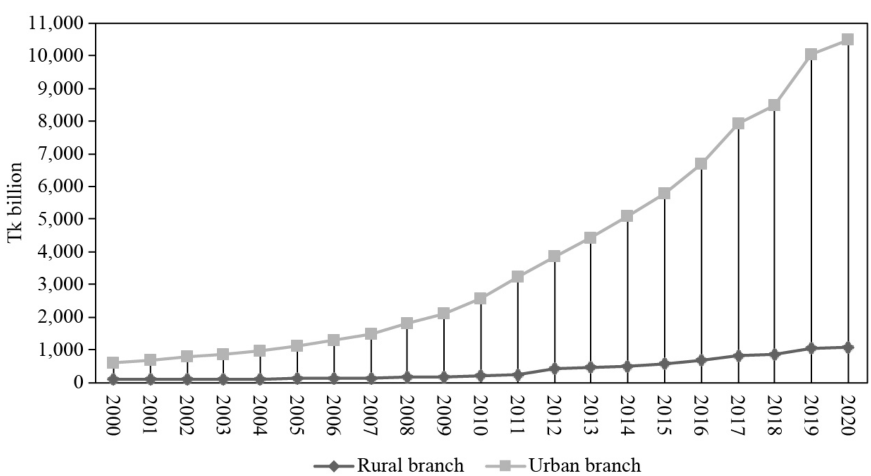
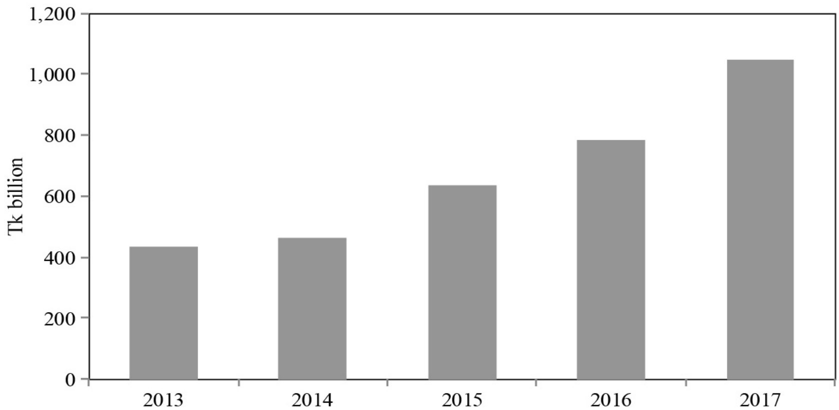
Appendix

Figure A1. **Disbursement of Loans through Rural and Urban Bank Branches**



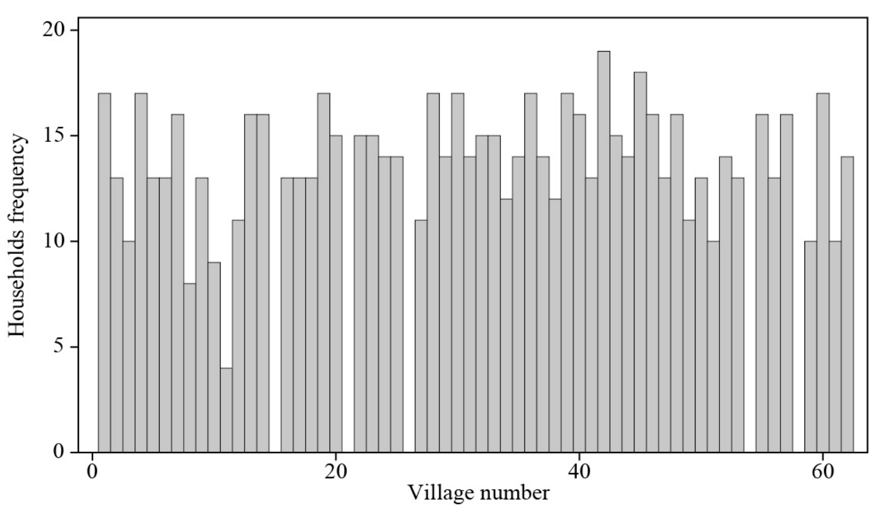
Tk = taka.
Note: Average exchange rate in 2020: $1 = Tk84.80.
Source: Microcredit Regulatory Authority. "Microfinance Information System Database." http://ndb.mra.gov.bd/mfi-dbms/ (accessed 10 May 2021).

Figure A2. **Total Microcredit Disbursement by Microfinance Institutions**



Tk = taka.
Note: Average exchange rate in 2020: $1 = Tk84.80.
Source: Microcredit Regulatory Authority. "Microfinance Information System Database." http://ndb.mra.gov.bd/mfi-dbms/ (accessed 10 May 2021).

Figure A3. **Frequency Distribution of the Repeat Households in the Study Villages**



Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A1. **Estimates of the Poverty Line: 1988, 2000, 2004, 2008, and 2014**

Reference Year of Survey	Estimated Income Poverty Line (current Tk)
1988	4,609
2000	7,023
2004	8,332
2008	15,194
2014	24,522

Tk = taka.
Source: Hossain and Bayes (2015, 2018).

Table A2. **Balance of the Covariates between the Treatment and Control Groups**

Household and Village Characteristics	Controls (C) (*N* = 512)		Treatment (T) (*N* = 279)		Mean Difference (T–C)	Normalized Difference
	Mean	SD	Mean	SD		
	(1)	(2)	(3)	(4)	(5)	(6)
Household size (no. of members)	5.998	2.97	6.287	2.665	0.289	0.102
Gender of household head (Male = 1, Female = 0)	0.951	0.22	0.964	0.186	0.013	0.064
Age of household head (years)	41.965	14.43	40.867	12.985	–1.097	–0.080
Education of head (years of schooling)	3.078	4.02	3.333	3.808	0.255	0.065
Highest education by a member of household	4.742	4.36	4.928	4.118	0.186	0.044
Share of working members in the household	0.316	0.16	0.275	0.133	–0.041	–0.275
Land owned by household (hectares)	0.729	1.04	0.654	1.069	–0.075	–0.071
Migration (if any member migrated = 1)	0.102	0.30	0.108	0.310	0.006	0.019
Distance to *upazila* (subdistrict) headquarters from village (km)	5.536	3.39	5.278	3.480	–0.258	–0.075
Electricity access (village has electricity = 1)	0.271	0.45	0.240	0.428	–0.031	–0.072
Rented-in land (hectares)	0.114	0.30	0.182	0.387	0.068	0.197
Total rice production (kg)	1,575	2,830.21	1,808	4,058	233	0.067
Total household income (Tk/year)	116,888	155,689	127,031	209,316	10,143	0.055
Poverty status (poor = 1, nonpoor = 0)	0.594	0.49	0.609	0.489	0.016	0.032
School enrollment rate for boys (6–10 years) (%)	56.111	47.35	57.310	47.661	1.199	0.025
School enrollment rate for girls (6–10 years) (%)	62.298	45.99	68.116	44.049	5.818	0.129

kg = kilogram, km = kilometer, SD = standard deviation, Tk = taka.
Note: This table examines the balance of the covariates in the first period (1988) using 791 households, comparing the means of covariates between the treatment and control groups.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A3. **Impact of Credit on Various Components of Household Income Using Panel Fixed Effects**

	(1) Crop	(2) Noncrop	(3) Wage	(4) Business	(5) Remittance
Panel A: Access to any credit (1 = yes, 0 = no)					
Current credit	0.324**	0.180	0.039	0.791***	–0.086**
	(0.130)	(0.117)	(0.229)	(0.213)	(0.036)
First credit lag	–0.134	0.017	–0.097	–0.168	0.057*
	(0.133)	(0.112)	(0.221)	(0.231)	(0.032)
Second credit lag	–0.154	–0.150	0.405*	–0.400*	–0.025
	(0.125)	(0.107)	(0.209)	(0.214)	(0.034)
Differential impact (credit dummy for each credit source)					
Panel B: Bank credit dummy (1 = yes, 0 = no)					
Current credit	0.087	–0.087	–0.288	0.303	–0.027
	(0.219)	(0.240)	(0.462)	(0.462)	(0.071)
First credit lag	0.313	0.124	0.001	0.116	0.042
	(0.202)	(0.186)	(0.380)	(0.395)	(0.047)
Second credit lag	0.092	–0.173	0.735**	0.268	–0.085
	(0.165)	(0.153)	(0.337)	(0.405)	(0.056)
Panel C: MFI credit dummy (1 = yes, 0 = no)					
Current credit	0.321*	0.235*	0.074	1.239***	–0.056
	(0.159)	(0.131)	(0.267)	(0.262)	(0.036)
First credit lag	–0.130	0.028	–0.070	0.012	0.044
	(0.166)	(0.150)	(0.273)	(0.288)	(0.040)
Second credit lag	–0.347*	–0.137	0.161	–0.564*	0.039
	(0.185)	(0.162)	(0.295)	(0.281)	(0.040)
Panel D: Informal credit dummy (1 = yes, 0 = no)					
Current credit	0.272	0.068	0.342	0.034	–0.086
	(0.182)	(0.171)	(0.320)	(0.283)	(0.053)
First credit lag	–0.269	–0.171	–0.231	–0.343	0.099**
	(0.195)	(0.162)	(0.310)	(0.343)	(0.49)
Second credit lag	0.049	–0.024	0.279	–0.432	–0.026
	(0.166)	(0.131)	(0.252)	(0.280)	(0.044)

MFI = microfinance institution.
Notes: Household and village characteristics are controlled for. Year and household fixed effects are applied to both panels. Robust standard errors are clustered at the household level and are presented in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. The total number of observations for all panels was 2,373.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A4. **Lagged Credit (first lag) Impact on Household Welfare—Controlling for Current Credit Access**

Main Household Welfare Indicator	(1) Any Credit	(2) Bank	(3) MFI	(4) Informal
Rented-in land (log)	–0.152	0.168	–0.126	–0.352**
	(0.103)	(0.191)	(0.123)	(0.146)
Total rice production (log) (kg)		–0.042	–0.128	–0.319
	(0.162)	(0.334)	(0.193)	(0.225)
Total household income (log) (Tk)	0.048	0.051	0.074*	0.005
	(0.033)	(0.061)	(0.040)	(0.051)
Poverty status (poor = 1, nonpoor = 0)	–0.032	–0.023	–0.042	–0.006
	(0.024)	(0.042)	(0.039)	(0.035)
Girls school enrollment rate (6–10 years)	–0.140	–0.375	–0.088	–1.154
	(2.588)	(2.755)	(3.532)	(3.278)
Boys school enrollment rate (6–10 years)	–4.112	2.855	–4.122	–3.935
	(4.831)	(3.519)	(6.624)	(7.696)

kg = kilogram, MFI = microfinance institution, Tk = taka.

Notes: Household and village characteristics are used as control variables in all regressions, with year and household fixed effects. Robust standard errors are clustered at the household level. ** = $p < 0.05$, * = $p < 0.1$. The number of observations for all outcomes is 2,373—except for education outcomes (girls enrollment, 772; boys enrollment, 570).

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A5. **Lagged Credit (second lag) Impact on Household Welfare—Controlling for Current Credit Access**

Main Household Welfare Indicator	(1) Any Credit	(2) Bank	(3) MFI	(4) Informal
Rented-in land (log)	–0.048	–0.080	–0.232*	0.222*
	(0.094)	(0.164)	(0.132)	(0.117)
Total rice production (log) (kg)	–0.045	–0.097	–0.246	0.251
	(0.151)	(0.264)	(0.224)	(0.181)
Total household income (log) (Tk)	–0.031	0.044	–0.038	–0.070*
	(0.035)	(0.065)	(0.043)	(0.040)
Poverty status (poor = 1, nonpoor = 0)	0.015	–0.003	0.008	0.037
	(0.022)	(0.039)	(0.030)	(0.028)
Girls school enrollment rate (6–10 years)	–2.281	–1.855	–3.162	–0.690
	(2.008)	(4.049)	(3.343)	(1.912)
Boys school enrollment rate (6–10 years)	–1.182.203	0.376	–6.442	0.364
	(3.624)	(3.570)	(4.845)	(5.222)

kg = kilogram, MFI = microfinance institution, Tk = taka.

Notes: Household and village characteristics are used as control variables in all regressions, with year and household fixed effects. Robust standard errors are clustered at the household level. * = $p < 0.1$. The number of observations for all outcomes is 2,373—except for education outcomes (girls enrollment, 772; boys enrollment, 570).

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A6. **Lagged Credit (second credit lag) Impact on Welfare Indicators Using Unbalanced Panel**

	Rented-in Land	Total Rice Production	Income	Poverty	School Enrollment Rate: Girls	School Enrollment Rate: Boys
Panel A: Access to any credit (lagged credit)						
Any credit	–0.035	–0.148	0.023	–0.007	–1.812	–1.537
	(0.069)	(0.116)	(0.025)	(0.016)	(1.751)	(3.195)
Observations	3,985	3,985	3,985	3,985	1,284	995
R-squared	0.030	0.131	0.208	0.102	0.033	0.020
Panel B: Differential impact (lagged credit dummy for each source)						
Bank credit	–0.023	–0.023	0.006	–0.002	–0.344	–0.197
	(0.126)	(0.232)	(0.045)	(0.029)	(3.161)	(4.285)
MFI credit	0.070	–0.222	0.046	–0.029	–2.294	0.141
	(0.097)	(0.159)	(0.034)	(0.023)	(2.078)	(4.609)
Informal credit	–0.094	–0.049	0.004	0.008	–1.873	–4.051
	(0.088)	(0.157)	(0.033)	(0.021)	(2.358)	(4.062)
Observations	3,985	3,985	3,985	3,985	1,284	995
R-squared	0.031	0.131	0.208	0.103	0.034	0.023

MFI = microfinance institution.
Notes: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at the household level. Second lag of credit access is used to identify longer-term impact.
Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.

Table A7. **Lagged Credit (third credit lag) Impact on Welfare Indicators**

	Rented-in Land	Total Rice Production	Income	Poverty	School Enrollment Rate: Girls	School Enrollment Rate: Boys
Panel A: Access to any credit (lagged credit)						
Any credit	–0.152	–0.171	–0.054	0.047	1.570	–2.429
	(0.128)	(0.214)	(0.046)	(0.031)	(3.128)	(7.347)
Observations	1,582	1,582	1,582	1,582	509	353
R-squared	0.040	0.072	0.213	0.143	0.116	0.366
Panel B: Differential impact (lagged credit dummy for each source)						
Bank credit	0.351*	0.305	0.035	0.023	–1.821	5.952
	(0.200)	(0.362)	(0.106)	(0.054)	(3.385)	(10.151)
MFI credit	–0.142	–0.425	–0.040	0.027	5.381	24.961
	(0.187)	(0.311)	(0.064)	(0.046)	(5.138)	(17.620)
Informal credit	–0.340**	–0.154	–0.034	0.003	–0.311	–22.401**
	(0.166)	(0.274)	(0.057)	(0.039)	(3.555)	(9.842)
Observations	1,582	1,582	1,582	1,582	509	353
R-squared	0.049	0.075	0.212	0.141	0.123	0.482

MFI = microfinance institution.

Notes: Household and village characteristics are used as control variables in all regressions with year and household fixed effects. Robust standard errors are clustered at the household level. ** = $p < 0.05$, * = $p < 0.1$. Third lag of credit access is used to identify longer-term impact.

Source: Authors' calculations from five rounds of the Mahabub Hossain Panel Data.