The Impact of Microcredit on Household Welfare: Evidence from Bangladesh during the COVID-19 Pandemic*

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Abstract

The onslaught of COVID-19 and the subsequent economic fallout have exacerbated world inequality, with the poor bearing a disproportionate brunt of the pandemic. In this paper, we investigate whether access to credit—in the form of microloans—cushioned the blow induced by COVID-19 and increased poor households' welfare. In particular, we use survey data on microloan borrowers in Bangladesh to examine how access to microfinance affected its clients during the COVID-19 crisis. We employ a difference-in-differences (DID) methodology to compare borrowers who received loans after the outbreak of the pandemic with borrowers who did not. Our results suggest that receiving microloans increases business earnings, food security, as well as food expenditure. These effects are primarily driven by borrowers of business-focused loans, while the impact of the loans focused on poverty reduction is muted.

Keywords: COVID-19, microcredit, poverty, BRAC, Bangladesh

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* This study uses primary data collected over the phone. All respondents of this survey were members of the BRAC Microfinance (MF) program. BRAC MF also reviewed the questionnaire extensively and provided essential feedback, which was duly addressed by BIGD. Being well aware of the research scope, BRAC MF provided BIGD with the necessary approval and contact details of the members of the BRAC MF program to conduct the survey. All respondents were surveyed upon their verbal consent and no respondent was surveyed without their stated permission.

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1. Introduction

South Asia holds a leading position in the global microfinance landscape, boasting the largest number of borrowers (85.6 million in 2018) and the top two markets (Bangladesh and India). Microcredit has been hailed for promoting financial inclusion among the poor and contributing to poverty alleviation. It now serves approximately a quarter of the population in Bangladesh—the context of this study.[i]

The advent of COVID-19, however, has thrown into sharp relief the precarity of poor borrowers and their access to microcredit. Newspaper reports and anecdotes abound regarding the turmoil in microfinance institutions (MFIs) during COVID-19. Academic literature on the issue, however, is surprisingly scant, particularly with regard to its effect on borrowers. Aggregate global data show a decrease in the efficiency of MFIs and a simultaneous increase in non-repayment (Zheng & Zhang, 2021). In Pakistan, 70% of borrowers failed to repay loans two months after the onset of the pandemic (Malik et al., 2020). In the context of our study, using administrative data from BRAC in Bangladesh, we find that at least 30% of borrowers were either delinquent or in default on their loans 12 months after the pandemic.

Our research examines the impact of receiving microloans during the COVID-19 pandemic on the lives of borrowers. Due to COVID-19 infections, a general holiday came into effect on 26 March 2020, and all microfinance operations in the nation stopped. In mid-May, microfinance operations and activity picked up again on a very small scale, when the program primarily attempted to refund the savings of borrowers and disbursed loans on a very limited basis. In August 2020, however, the program started to disburse refinancing loans. Refinancing was available for clients whose

businesses had been impacted by the pandemic or other natural disasters, leading to a decrease in their regular income. In this paper, we study the impact of the refinancing loan. We use administrative data from BRAC—the largest non-governmental organization (NGO) in the world and the biggest microfinance lender in Bangladesh. We then conduct a survey among a sample of 10,794 randomly selected households from the pool of borrowers who were borrowing from BRAC Microfinance in 2019, before the onset of COVID-19. Employing a difference-in-differences (DID) strategy, we compare borrowers who borrowed *only* in the pre-lockdown period against borrowers who successfully borrowed in *both* the pre- and post-lockdown periods to investigate the effect on household welfare and business earnings. We focus on borrowers of BRAC's two major microfinance products: (a) *Dabi* (loans given to low-income women to buy productive assets, invest in businesses or property, smooth consumption, or manage shocks), and (b) *Progoti* (loans given to relatively wealthier men or women for enterprise development).[ii]

Our results indicate that food security, expenditure, and business profits increase significantly for households that receive microloans from BRAC after the advent of COVID-19.

However, there exists substantial heterogeneity in the impacts on business profits with respect to the size of the loan. The effects of both *Progoti* and *Dabi* loans are positive and statistically significant for those who took smaller loans (loan size smaller than the median loan size). There is no statistically significant effect for those who took larger loans.

We find that the nature of microcredit usage during the pandemic differed by the gender of the borrower. Exploiting the feature of the *Progoti* loan, where borrowers can be of either gender, we find that households with a male borrower have higher business profits, while households with female borrowers did not experience any significant increase. On the other hand, food expenditure

improved significantly for households with female borrowers, which did not occur for households with male borrowers.

As data unavailability precludes us from formally testing for similar pre-trends in outcome variables, we conduct a robustness check of our results following Sant'Anna and Zhao (2020) and find that our findings are robust.

This paper contributes to three strands of the literature. First, it broadly relates to the literature on the impact of microloans in general. Since its inception and subsequent proliferation, microfinance has garnered extensive academic interest, and a large body of evidence exists on its effects on households. While initial estimates indicated large positive results on household welfare and business profits (Pitt & Khandker, 1998), these findings came under scrutiny for endogeneity and persistent selection bias (Roodman & Morduch, 2014). Bateman and Chang (2012) critique the contemporary microfinance model, arguing that while there may be some short-term benefits for a small minority of individuals, it ultimately has serious limitations as a development policy and can act as a "poverty trap." More rigorous evaluations, however, have been conducted over the last decade, with results indicating moderate impacts. In a review of results from six randomized controlled trials (RCTs) of microcredit interventions, Banerjee et al. (2015) note a "consistent pattern of modestly positive, but not transformative effects." Jointly estimating the average effect and heterogeneity, Meager (2019) finds similar results using the Bayesian hierarchical model. More recent analyses, however, point to a more nuanced understanding, with significant heterogeneity in impacts. For talented entrepreneurs, access to credit can indeed facilitate escape from poverty traps (Banerjee et al., 2019).

Second, this work also speaks to a large body of literature on the impact of credit during economic shocks and stressors. Households' ability to overcome constraints and make investments

depends on the set of financial services available to them (Conning & Udry, 2007). Theoretical results recognize credit's ability to act as a buffer against income fluctuations (Deaton, 1991). During an unanticipated income shock, credit card loans increased in Singapore (Agarwal & Qian, 2014). More recent and related work empirically demonstrates that loan products from BRAC, which guarantee access to credit following a negative shock, increase household welfare (Lane, 2020). Results from our analysis relate to this body of work in the context of COVID-19 and empirically demonstrate that receiving microloans during an economic crisis, such as the pandemic, is associated with increased income and food security.

Finally, our research relates to the literature on the impact of loans during the pandemic. The Paycheck Protection Program (PPP) in the United States (US)—a fiscal stimulus enacted by Congress to aid small businesses through loans in response to COVID-19—generated significant positive effects (Autor et al., 2022). In Iran, emergency loans in response to the pandemic were positively related to higher consumption, particularly for the poorer segment of the population (Hoseini & Beck, 2020). We supplement this emerging literature by documenting how access to microloans during COVID-19 increased household welfare and business profits.

The rest of the paper is organized as follows: Section 2 describes the context and BRAC's microfinance program. In Section 3, we present the study design. In Section 4, we discuss the data and provide descriptive statistics. Section 5 outlines our empirical strategy. In Section 6, we discuss results, in addition to presenting heterogeneity analysis and a robustness check. Section 7 concludes the paper.

2. Context

2.1. COVID-19 in Bangladesh

The first COVID-19 case in Bangladesh was identified in early March 2020 (BIGD-ARC, 2021). To curb infections, the government declared a "general holiday" that came into effect on 26 March 2020. The general holiday was extended several times throughout April and May, until officially ceasing on 30 May 2020. In June 2020, economic activities started to resume as the government relaxed lockdowns. The number of positive cases peaked in August 2020 and started to decline afterwards. However, cases began to rise again in March 2021, starting the "second wave" of COVID-19 in Bangladesh. This led the government to impose new lockdowns in April 2021, which continued, with brief interruptions, until August 2021.

2.2. Microfinance in Bangladesh

Microcredit has expanded rapidly in Bangladesh over the last three decades. According to statistics from the Microcredit Regulatory Authority (MRA), the total number of borrowers was 6.7 million in 2000, which increased to 19.21 million in 2010 and stabilized at 22 million in 2017. This renders a quarter of the population dependent on MFIs for access to credit. In terms of microfinance market saturation, Bangladesh has consistently topped the global list (Bateman, 2012).

2.3. BRAC Microfinance

In Bangladesh, BRAC is the largest microfinance lender. As of 2023, BRAC Microfinance has 11 million members, with loan disbursement totalling at approximately USD 6 billion.[iii] BRAC is currently operating out of over 2,000 locations across all 64 districts of Bangladesh.

While BRAC offers a variety of microloan products, the two most popular are *Dabi* and *Progoti*. We restrict our research analysis in this paper to *Dabi* and *Progoti* borrowers. Below, we describe the features of these loans:[iv]

1. ***Dabi*:** This is BRAC's largest loan product in terms of the number of borrowers. Loan recipients are exclusively women. BRAC forms village organizations consisting of around 15–25 women from local communities. *Dabi* loans range from USD 170 to USD 2,500. Typical *Dabi* instalments are collected weekly, but in regions with better socio-economic conditions, BRAC has switched to monthly instalments. *Dabi* loans are disbursed to help low-income women buy productive assets, invest in business or property, smoothen consumption, or manage shocks.
2. ***Progoti*:** This is BRAC's primary microloan product in terms of total loan portfolio value. *Progoti* is an enterprise loan targeted towards existing small enterprises, and there is no mandate restricting beneficiaries to only women. Thus, recipients may be men or women. The size of *Progoti* loans is much larger compared to *Dabi*, ranging from USD 1,400 to USD 13,000.

2.4. Microfinance during COVID-19

When the government declared a general holiday on 26 March 2020, all microfinance operations in the country stopped. A moratorium on both loan disbursement and loan repayment was promulgated and remained in effect until mid-May. Microfinance operations and activity picked up again at a small scale in mid-May 2020, when the program mainly attempted to refund the savings of the borrowers and disbursed loans on a limited basis. This continued until the end of

July 2020. In August 2020, the program started to disburse refinancing loans. The loan tenure for these refinancing loans was 9, 12 or 18 months.

Refinancing was available to clients whose businesses had been impacted by the pandemic or other natural disasters, leading to a decrease in their regular income. This enabled borrowers to access funds to support their income-generating activities (IGAs) and navigate the economic downturn. The main eligibility criteria for the refinancing loans were as follows:

- Repeat borrowers, i.e., current borrowers who had borrowed at least once in the past and maintained good standing until February 2020, were considered for refinancing. Eligible borrowers were those affected by the pandemic or any other natural disaster and who had the willingness to repay the loan despite interrupted income flow.
- Refinancing facilities were provided to those who had either (i) a 12-month-term loan and repaid 4–9 instalments, or (ii) a 46-week-term loan and repaid 7–36 instalments, or (iii) an 18-month-term loan and repaid 4–15 instalments.

To be eligible for a refinancing loan, a borrower needed to meet all of the above criteria. Initially, these refinancing loans were disbursed until December 2020, but they were later continued on a limited scale from January 2021 to March 2023. Since some borrowers were ineligible for the refinancing loans, a significant fraction of existing borrowers (i.e., those who had borrowed before the pandemic) did not have access to microcredit in 2020. In our analysis using administrative data, we find that while in a typical year, 80% of borrowers renew their loans the following year, this figure fell to 60% during 2020—even after accounting for the loan repayment moratorium.

3. Study Design

We use a difference-in-differences (DID) strategy to evaluate the impact of microloans during COVID-19. We restrict our analysis to the pool of *Dabi* and *Progoti* borrowers who were clients of BRAC MF in 2019, before the advent of the pandemic.

We define our treatment group as those borrowers who received refinancing microloans after the lockdown and loan moratorium in 2020, and our comparison group as those borrowers who did not receive such loans after the lockdown in 2020. Thus, we compare households that were beneficiaries of microloans after the onset of the pandemic with households that were not, leveraging the decline in microcredit borrowing during the pandemic as explained above.

Since these two groups may differ in both observable and unobservable characteristics, a simple comparison of post-lockdown means would yield a biased estimate. Thus, we resort to a DID strategy to estimate the impacts of the program. Our identification strategy hinges on the assumption that the underlying trends in outcomes between the treatment and comparison groups would have been similar in the absence of access to microfinance (i.e., the parallel trends assumption).

While our survey data do not allow us to fully validate parallel trends for all our outcomes of interest before the pandemic-induced lockdowns, we nonetheless provide suggestive evidence in support of this assumption using pre-COVID administrative data on loans. Moreover, we use a doubly robust difference-in-differences (DRDID) method to check the robustness of our main DID results.

4. Data and Descriptive Statistics

4.1. Data Collection

We use both administrative and survey data for our analysis. Administrative data are sourced from BRAC's management information system (BRAC MIS), while household welfare and business data are collected through a survey.

To draw our sample, we first randomly selected 300 branches from BRAC's 2,757 branch offices across the country. BRAC disburses *Progoti* loans in all these branches and *Dabi* loans in 274 of these branches. We then used administrative data from BRAC MIS to identify a random sample of 60 *Dabi* borrowers from the 274 branches with *Dabi* borrowers and 25 *Progoti* borrowers from all 300 branches. We interviewed these selected borrowers over the phone. We opted for phone surveys to minimize health risks due to COVID-19 and to eschew unforeseen circumstances owing to sudden lockdowns.

We conducted the survey from July to September 2021 and collected recall data ranging over pre- and post-lockdown periods. We collected information on income, expenditure, food security, business profits, and other primary household socioeconomic characteristics. Further details of the timeline of the data collected on different outcome variables can be found in Table 1.

We initially attempted to reach a sample of 23,016 households, but due to non-response, we surveyed a total of 10,794 households. Appendix Table A1 compares the characteristics of households that were successfully surveyed with those that were not. The results show statistically significant differences in age and gender of respondents between the two groups of *Progoti* borrowers. For *Dabi*, only gender shows a statistically significant difference. For other variables,

there is no statistically significant difference. These results raise some concerns about the external validity of the results, particularly for *Progoti* borrowers. Nonetheless, we estimate the heterogeneity of effects with respect to gender in our results to assess whether they vary by gender. Of our surveyed respondents, 6,793 were *Dabi* borrowers and 4,001 were *Progoti* borrowers. Based on our definition of treatment and comparison groups stated above, 5,771 households are in the treatment group, while 5,023 are in the comparison group. One potential concern is whether poorer households were more likely to be attrited from the survey. This is perhaps unlikely, as the principal loan amounts are similar across surveyed and attrited households (Table A1). Generally, poorer households tend to borrow smaller loans from MFIs. Analyzing our survey data, we find that there is a strong negative correlation between loan size during COVID and pre-COVID food insecurity, indicating that poorer households take smaller loans.

As we have used recall data for our outcome variables, another concern is the possibility of recall bias, which could affect the impact estimates. However, we use recall data from both treatment and comparison groups. We thus assume that recall bias, if any, is similar across treatment and comparison groups, thereby not affecting our estimates. Moreover, both treatment and comparison groups were surveyed during the same time period. All of those who were successfully interviewed responded to all outcome variables, thereby allaying concerns related to non-response as well.

Table 1: Description of Outcome Variables

Outcome variables	**Description**	**Timeline**
Business earnings	Monthly profit from all the business activities that household members	Data collected for five different points in time from January–

	engaged in (BDT)	February 2020 to June 2021 **Pre-lockdown:** January–February 2020 **Post-lockdown:** (August–September 2020; December 2020–January 2021; April–May 2021; June 2021)
Food expenditure	Monthly total food expenditure of the household (BDT)	Data collected for four different points in time from January–February 2020 to April–May 2021 **Pre-lockdown:** January–February 2020 **Post-lockdown:** (August–September 2020; December 2020–January 2021; April–May 2021)

Food insecurity	If any of the household members had to consume a lower amount of food than needed due to financial hardship	Data collected for six different points in time from January–February 2020 to April–May 2021 **Pre-lockdown:** January–February 2020 **Post-lockdown:** (June–July 2020; September–October 2020; December 2020–January 2021; February–March 2021; April–May 2021)

4.2. Descriptive Statistics

We collected information on time-invariant characteristics as well as recall data on the socioeconomic condition of households before the pandemic. In Table 2 below, we provide descriptive statistics and also examine pre-existing differences between the treatment and comparison groups (before the outbreak of COVID-19).

Table 2: Baseline Characteristics of Sample Households

Variable	Treatment mean	Comparison mean	Difference in means (Treatment vs Comparison)
	(1)	(2)	(3=2-1)
Panel A: Full sample			
Household size (number of members)	4.959 (1.840)	4.916 (1.806)	-0.042 (0.035)
Respondent's age (years)	38.891 (10.435)	39.237 (11.151)	0.346* (0.207)
Respondent's years of schooling	6.011 (4.327)	6.146 (4.505)	0.134 (0.085)
Respondent female	0.729 (0.445)	0.721 (0.449)	-0.008 (0.009)
Household head's years of schooling	5.718 (4.602)	5.962 (4.744)	0.243*** (0.090)
Household head's age (years)	43.737 (11.210)	43.895 (11.702)	0.158 (0.221)
Female-headed household	0.118 (0.323)	0.131 (0.337)	0.013** (0.006)
Per capita monthly income (BDT)	5,898.479 (19190.98)	4,836.824 (25639.6)	-1,061.655** (432.705)
Household's cattle (number)	1.925 (3.283)	1.582 (3.005)	-0.343*** (0.061)
Household's poultry (number)	24.081 (329.319)	17.538 (412.301)	-6.544 (7.145)

Variable	Treatment mean	Comparison mean	Difference in means (Treatment vs Comparison)
	(1)	(2)	(3=2-1)
Household's agricultural machinery (number)	0.080 (0.726)	0.088 (1.175)	0.008 (0.019)
Per capita monthly food expenditure (BDT)	1,869.74 (813.913)	1,862.361 (855.975)	-7.378 (16.089)
Per capita monthly non-food expenditure (BDT)	1,897.464 (3509.814)	1,934.024 (3900.453)	36.560 (71.335)
N	5,771	5,023	
Panel B: Dabi			
Household size (number of members)	4.731 (1.608)	4.750 (1.655)	0.020 (0.040)
Respondent's age (years)	36.603 (9.700)	36.679 (10.379)	0.076 (0.244)
Respondent's years of schooling	5.234 (3.906)	5.228 (3.946)	-0.006 (0.096)
Respondent female	0.993 (0.082)	0.993 (0.084)	0.000 (0.002)
Household head's years of schooling	4.907 (4.306)	5.076 (4.342)	0.170 (0.106)
Household head's age (years)	42.887 (11.233)	42.701 (11.533)	-0.186 (0.278)
Female-headed household	0.123 (0.328)	0.137 (0.344)	0.014* (0.008)

Variable	Treatment mean	Comparison mean	Difference in means (Treatment vs Comparison)
	(1)	(2)	(3=2-1)
Per capita monthly income (BDT)	4,360.659 (4808.388)	4,122.887 (5742.962)	-237.771* (128.021)
Household's cattle (number)	1.524 (2.570)	1.305 (2.460)	-0.219*** (0.061)
Household's poultry (number)	10.019 (63.832)	9.114 (96.189)	-0.906 (1.953)
Household's agricultural machinery (number)	0.040 (0.326)	0.028 (0.399)	-0.012 (0.009)
Per capita monthly food expenditure (BDT)	1,728.84 (678.736)	1,712.659 (707.727)	-16.181 (16.867)
Per capita monthly non-food expenditure (BDT)	1,573.251 (2572.049)	1,605.66 (3662.128)	32.409 (75.888)
N	3,716	3,077	
Panel C: Progoti			
Household size (number of members)	5.371 (2.137)	5.179 (1.995)	-0.192*** (0.065)
Respondent's age (years)	43.028 (10.444)	43.283 (11.134)	0.255 (0.341)
Respondent's years of schooling	7.417 (4.683)	7.598 (4.933)	0.181 (0.152)
Respondent female	0.251 (0.434)	0.291 (0.454)	0.040*** (0.014)

Variable	Treatment mean	Comparison mean	Difference in means (Treatment vs Comparison)
	(1)	(2)	(3=2-1)
Household head's years of schooling	7.185 (4.756)	7.354 (5.010)	0.169 (0.155)
Household head's age (years)	45.272 (11.006)	45.774 (11.723)	0.502 (0.360)
Female-headed household	0.110 (0.313)	0.122 (0.327)	0.012 (0.010)
Per capita monthly income (BDT)	8,679.277 (31317.1)	5,965.695 (40535.67)	-2,713.581** (1,141.738)
Household's cattle (number)	2.650 (4.185)	2.019 (3.666)	-0.631*** (0.125)
Household's poultry (number)	49.510 (544.318)	30.858 (651.151)	-18.652 (18.936)
Household's agricultural machinery (number)	0.151 (1.131)	0.183 (1.815)	0.032 (0.048)
Per capita monthly food expenditure (BDT)	2,124.525 (962.732)	2,099.069 (1004.077)	-25.456 (31.095)
Per capita monthly non-food expenditure (BDT)	2,483.73 (4701.725)	2,453.229 (4198.984)	-30.500 (141.208)
N	2,055	1,946	

Note: Figures in parentheses are standard deviations (columns 1 and 2) and standard errors (column 3). ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A of Table 2 provides statistics for the pooled sample, while Panels B and C provide statistics for *Dabi* and *Progoti* borrowers, respectively. In line with our expectations, almost all *Dabi*

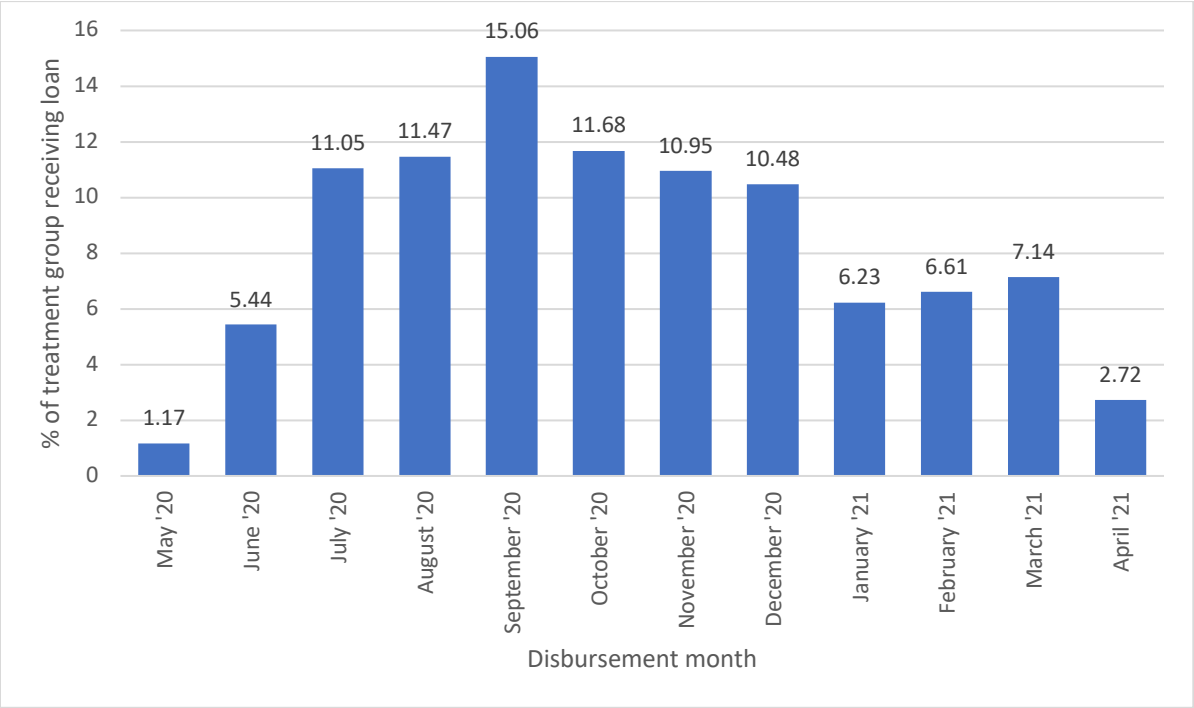
borrowers are female (99%), while most *Progoti* borrowers are male (73%). The average monthly earnings of the borrowers are lower than the national average monthly per capita income of BDT 7,614 (BBS, 2023), indicating that microfinance borrowers are on the lower rungs of the socioeconomic ladder.

Examining the pre-existing differences between the treatment and comparison groups, we find the treatment group to be significantly wealthier than the comparison group before the pandemic (Panel A of Table 2). Treatment group households are also likely to have more cattle and be less educated. Among *Progoti* borrowers, the percentage of females is significantly higher in the comparison group than in the treatment group, suggesting that women had more difficulty securing loans after the lockdown compared to men. This observation is consistent with previous findings on the gendered impact of the COVID-19 pandemic (Rahman et al., 2022).

There exists substantial heterogeneity between treatment and comparison groups, as shown in Table 2. However, as we are using double-difference, these pre-existing variations between the two groups are netted out in our treatment estimates, assuming that unobservables are time-invariant. Thus, we are able to tease out the effect of microloans as long as the parallel trend assumption holds, i.e., there are no differential time trends between treatment and comparison groups.

Another important piece of descriptive statistics is the timing of loan disbursements among our treatment respondents in 2020, which contextualizes observed outcomes. Figure 1 shows the distribution of loan disbursals by month. As discussed earlier, in May and June 2020, only a small number of respondents took loans; not until July 2020 did loan disbursement fully pick up. The majority of the respondents received their loans from July to December 2020. A small share (4%) of treatment participants took loans twice between May 2020 and April 2021.

Figure 1: Distribution of Loans Taken Across Months by the Treatment Group (N=5,771)



5. Estimation

5.1. Empirical Strategy

As discussed earlier, to evaluate the impact of access to microfinance, we utilize a DID approach. Specifically, we compare microfinance borrowers from 2019 who managed to secure loans after the pandemic (i.e., from May 2020 onwards) with microfinance borrowers from 2019 who did *not* manage to secure loans after the pandemic. We use the following regression equation:

$$y_{ilwt} = \alpha_i + \beta_1 Time_t + \beta_2 Treatment_{il} * Time_t + \beta_3 Rainfall_{lt} + \varepsilon_{ilwt}$$

where, α_i is the individual/household fixed effects; y_{ilwt} is the outcome variable of interest for household i in location (branch) l in survey wave w at time t such as income and food security; $Treatment_{il}$ is a binary variable taking the value 1 if household i in location l received a loan

after the lockdown and *0* otherwise; $Time_t$ is a dummy variable taking the value *1* if the time period is post-lockdown and *0* if the time period is pre-lockdown; $Rainfall_{lt}$ is the average rainfall in location l for the corresponding period (i.e., month-wise rainfall data averaged for the corresponding year). We control for rainfall as it may affect outcomes such as food security (Kinda and Badolo, 2019). Rainfall may also affect microcredit participation through reducing farm income (Ahmed, 2024). $Rainfall_{lt}$ thus captures the time variant effects of agro-climatic factors on both the outcomes and the independent variable of interest (microcredit participation). ε_{ilwt} is the stochastic error term.[v] Our coefficient of interest is β_2 on the interaction term, which captures the impact of microfinance under the parallel trends assumption.

5.2. Identification Strategy

The DID approach can identify unbiased estimates of the impact of treatment if the parallel trend assumption holds, i.e., the average outcomes for treatment and comparison groups would have moved in parallel if the treatment had not occurred. We do not have the data on outcome variables for multiple pre-intervention periods. Hence, we cannot explicitly test whether a pre-intervention parallel trend exists.

We can, however, provide suggestive evidence that parallel trends hold using administrative data from BRAC on two indicators: (i) the number of borrowers each year as a percentage of total borrowers in the sample, i.e., what share of the sample borrows each year, and (ii) the number of new borrowers each year as a percentage of total borrowers in that year, i.e., what share of borrowers in a year are new borrowers. In the absence of pre-trend analysis for the outcome variables, parallel trend analysis for these two variables is expected to provide some useful insights as the composition of new borrowers or borrowers in each year in total sample

households may affect household outcomes such as business income and/or food expenditures. For example, if loans are directly used for financing consumption expenditure, a non-parallel trend in the composition of new borrowers or borrowers in total borrowers is likely to indicate a non-parallel trend in food consumption. Hence, we use these two indicators to provide insights for the parallel trends in the outcome variables of interest. Appendix Figures F1 through F4 show the two indicators separately for *Dabi* and *Progoti*. They show that parallel trends exist for one variable for both *Dabi* and *Progoti* (Figures F1 and F2).

We also compound our analysis using DRDID following Sant'Anna and Zhao (2020). After adjusting for covariates, this model provides an unbiased estimate if the propensity score matching (PSM) is correct, even if the outcome modelling is wrong. We reproduce all our results using this methodology in Section 6. It is important to note that our impact estimates—particularly those through using simple DID—can be upwardly biased since the treatment group, which had higher income and assets at baseline, could show higher resilience relative to the comparison group in the absence of the program. While the DRDID results provide a robustness check of this, one cannot fully rule out the possibility of any unobserved time-variant heterogeneity, which may lead to better resilience among the treatment group, thereby upward-biasing the results.

6. Results

In this section, we discuss the findings from the analyses. Specifically, we look into the effects on business income, food expenditure, and food security.

6.1. Business Income

Given that a core assumption underlying microloans is that the credit disbursed should be used for IGAs, we first investigate whether access to microfinance impacts business profits. In Table 3, we present the main findings of our paper. The dependent variable is the inverse hyperbolic sine transformed value of the monthly business income. Our survey gathered data on business profits over five distinct time periods, each anchored to significant events to aid respondent recall (before lockdown, immediately after lockdown, after the annual religious festival, year-end, and the last month before the survey). Our pre-lockdown measure of business profit is thus recall data as reported by respondents on business income before the lockdown, while our post-lockdown measure is the business profit over the four periods recalled in the data. The specific range of months for which data has been collected can be found in Table 1. We use an inverse hyperbolic transformation approach to deal with outliers in the data. Appendix Figure F5 shows the distribution of monthly profits of the households surveyed in all rounds.

Column 1 of Table 3 shows our results for the pooled sample of borrowers. Our findings indicate that access to microloans significantly impacts business income. Households that managed to take a loan after the outbreak of the pandemic earned 9.15% more from their businesses than households that did not take a loan. In Columns 2 and 3, we segregate our data by *Dabi* and *Progoti* borrowers, where the impact on business profits for both *Dabi* and *Progoti* is statistically insignificant. The point estimates, however, indicate that the effect for the pooled sample is mainly driven by the effect of *Progoti* loans.

Table 3: Impact on Business Earnings

	(1) Full sample	(2) Dabi	(3) Progoti
Received loan*Post	0.0915**	0.0370	0.139
	(0.0463)	(0.0516)	(0.0888)
Constant	3.868***	2.902***	5.497***
	(0.0215)	(0.0240)	(0.0411)
N	53,970	33,965	20,005
R-squared	0.025	0.018	0.037

Note: Figures in parentheses are standard errors. The dependent variable here is the inverse hyperbolic sine transformed value of the profit amount (in BDT). We control individual and time-fixed effects and rainfall.
∗ p < 0.10, ∗∗ p < 0.05, ∗∗∗ p < 0.01

To assess whether loan size has any impact on the outcome, we conduct a heterogeneity analysis by dividing the *Dabi* and *Progoti* borrowers into two groups based on their loan size (with larger loans defined as those above the median). Results from the heterogeneity analysis are reported in Table 4.

Table 4: Heterogeneity of the Effects on Business Earnings with Respect to Loan Size

	(1) Dabi	(2) Progoti
Large loan*Post	-0.0675	0.0922
	(0.0590)	(0.101)
Small loan*Post	0.190***	0.218*
	(0.0666)	(0.120)
Constant	2.904***	5.497***
	(0.0240)	(0.0411)
N	33,965	20,005
R-squared	0.018	0.037

Note: Figures in parentheses are standard errors. The dependent variable here is the inverse hyperbolic sine transformed value of the profit amount (in BDT). We control individual and time-fixed effects and rainfall.

∗ p < 0.10, ∗∗ p < 0.05, ∗∗∗ p < 0.01

Results show that *Progoti* borrowers with a loan size smaller than the size of the median loan have significantly higher business earnings compared to the comparison group. A similar pattern holds for *Dabi* borrowers: those smaller-than-median loan sizes show a significant positive effect, while those with larger-than-median loans do not.

6.2. Food Expenditure

Next, we examine how access to credit impacts consumption, in particular, food expenditure. Employing a similar methodology as used earlier for business earnings, we gathered food expenditure recall data over four distinct periods in 2020–2021 for our pre- and post-lockdown measures. In Column 1 of Table 5, we estimate the impact on our pooled sample, where the dependent variable is the natural log of monthly per capita food expenditure. Our findings indicate that households that took microloans after the onset of the pandemic had higher expenditures on food.

Table 5: Impact on Food Expenditure (Log)

	(1)	(2)	(3)
	Full sample	Dabi	Progoti
Received loan*Post	0.00974**	0.0103*	0.0112*
	(0.00429)	(0.00577)	(0.00618)
Constant	7.448***	7.380***	7.563***
	(0.00193)	(0.00260)	(0.00278)
N	43,176	27,172	16,004
R-squared	0.019	0.024	0.012

Note: Figures in parentheses are standard errors. The dependent variable here is the logarithm of per capita food expenditure (in BDT). We control individual and time-fixed effects and rainfall.

$* p < 0.10$, $** p < 0.05$, $*** p < 0.01$

The results for the full sample are modest and significant at a 5% level. Households that took a loan consumed 0.97% more on food, compared to households that did not take microcredit. When we separate our results by *Dabi* and *Progoti* beneficiaries in Columns 2 and 3, respectively, our estimates indicate that the effects on both *Dabi* and *Progoti* borrowers are statistically significant—a 1.03% and 1.12% increase in food expenditure.

6.3. Food Insecurity

Table 6 reports our results for the impact of microcredit on food insecurity. Unlike the previous outcomes variables—business income and food expenditure—which are objective measures, our measure on food security is subjective. Here, we ask respondents about their *perceived* status of food insecurity. Specifically, respondents reported whether they felt they had to consume less than the necessary amount of food in a particular time period. We divided our time periods over six distinct, easily recalled phases. The dependent variable is a binary outcome, indicating whether a household reported consuming less than required or otherwise.

Table 6: Impact on Food Insecurity

	(1) Full sample	(2) Dabi	(3) Progoti
Received loan*Post	-0.0117*	-0.00593	-0.0307***
	(0.00609)	(0.00819)	(0.00873)
Constant	0.104***	0.124***	0.0683***
	(0.00288)	(0.00387)	(0.00412)
N	64,752	40,751	24,001
R-squared	0.097	0.115	0.067

Note: Figures in parentheses are standard errors. The dependent variable here is an indicator variable of whether the household had to consume a lower-than-usual amount of food due to poverty. We control individual and time-fixed effects and rainfall.

$*$ p < 0.10, $**$ p < 0.05, $***$ p < 0.01

Column 1 of Table 6 indicates that perceived food insecurity decreases significantly for those households that took microloans. When looking at segregated results by *Dabi* and *Progoti* in Columns 2 and 3, our estimates appear effectively driven by *Progoti* beneficiaries, whereas the *Dabi* beneficiaries show muted and insignificant effects. The impact on food security is much larger for the *Progoti* sample.

6.4. Heterogeneity by Gender

We have described in Section 2.3 that *Dabi* borrowers are exclusively female, while no such rule or restriction exists for *Progoti*. In our sample, approximately 73% of the *Progoti* borrowers are male.[vi] This provides us with enough observations and allows for analyses segregated by gender. In this section, we look into the impact on business earnings and food expenditure by segregating the *Progoti* sample among males and females.

Column 1 of Table 7 (where the dependent variable is the inverse hyperbolic sine transformed value of the monthly business income) shows that male *Progoti* borrowers experienced a statistically significant increase of 27.6% in business earnings, while there is no significant impact for female *Progoti* borrowers (Column 2). This implies that male borrowers are more inclined to allocate their microloans efficiently to their businesses, leading to higher earnings. This finding is consistent with findings reported by de Mel et al. (2008), which showed that male-owned microenterprises in Sri Lanka saw significantly larger returns from randomized grants, while no positive returns were found for those owned by females.

Table 7: Impact on Business Earnings for *Progoti*

	(1)	(2)
	Male	Female
Received Loan*Post	0.276**	-0.150
	(0.112)	(0.128)
Constant	6.537***	2.590***
	(0.0499)	(0.0571)
N	14,595	5,410
R-squared	0.045	0.016

Note: Figures in parentheses are standard errors. The dependent variable here is the inverse hyperbolic sine transformed value of the profit amount (in BDT). We control individual and time-fixed effects and rainfall.

$* p < 0.10$, $** p < 0.05$, $*** p < 0.01$

The heterogeneous impacts on business earnings with respect to the gender of borrowers raise the question of where female borrowers spend their microloans. When we look at the household food consumption, we find that food expenditure increases by 2.6% for households with female borrowers (Table 8), while there is no significant impact for male borrowers.

Table 8: Impact on Food Expenditure for *Progoti* (Log)

	(1)	(2)
	Male	Female
Received Loan*Post	0.00553	0.0258**
	(0.00728)	(0.0117)
Constant	7.576***	7.529***
	(0.00315)	(0.00505)
N	11,676	4,328
R-squared	0.012	0.015

Note: Figures in parentheses are standard errors. The dependent variable here is the logarithm of per capita food expenditure (in BDT). We control individual and time-fixed effects and rainfall.

$*$ p < 0.10, $**$ p < 0.05, $***$ p < 0.01

Combining the findings from the two tables, our results indicate that females spend their loans on food expenditure, while males spend their loans on businesses. This finding provides us with a possible explanation behind the muted impact on business profits for *Dabi* in contrast to the large point estimates for *Progoti*. Since all *Dabi* borrowers are female, their spending behaviour on businesses might contribute to the results.

6.5. Heterogeneity by Treatment Timing

A fraction of borrowers in our treatment group obtained their loans earlier in 2020. In Table A2, we present the heterogeneity of the effects of loans with respect to treatment timing. We categorize the treatment timing as early (loans before October 2020) and late (loans taken in October 2020 and onwards) and estimate a single DID equation for key outcomes using these groups. The results

suggest that perceived food insecurity significantly decreases for borrowers receiving loans earlier in the case of *Progoti*. However, there is no significant impact on business earnings and food expenditure separately for early and late loan takers.

6.6. Robustness Checks

As mentioned previously, due to data unavailability, we could not test if there is a parallel trend in the outcome variables before the pre-intervention period. Hence, we provide a robustness check of our results by using doubly robust difference-in-differences (DRDID) proposed by Sant'Anna and Zhao (2020). Contrary to simple DID estimators, DRDID estimators remain consistent if either a propensity score or outcome regression working model is correctly specified, without the requirement for both to be accurately specified simultaneously. If we assume that the parallel trends assumption holds after conditioning on pre-treatment characteristics, the DRDID provides an unbiased estimate of the program impacts.

As discussed earlier, our data collection encompassed recall data for the outcome variables for both pre- and post-lockdown timeframes, with multiple time periods for the endline (post-lockdown). For the DRDID regression analysis, we calculated the mean of the endline values and constructed two rounds of panel data. We incorporated the following covariates in the regression: the gender, age, and education of both the household head and the borrower; household size; per capita monthly income; per capita monthly food expenditure; per capita monthly non-food expenditure; and the number of cattle, poultry, and agricultural machinery.

The DRDID findings are presented in Tables 9 through 11.[vii] We find statistically significant results across all outcome variables—business profit, food expenditure, and food security—for the entire sample. These results are consistent with the simple DID results discussed

previously. Among *Progoti* borrowers, we observe statistically significant results at 10% and 1% levels for food expenditure and food security respectively in the simple DID analysis, with business income showing no significance. However, in the DRDID analysis, we find statistically significant effects on all three outcome variables for the *Progoti* sample. Hence, for the *Progoti* sample, the DRDID results are qualitatively similar to the simple DID results. Similar findings are observed for the *Dabi* sample.

Table 9: Impact on Business Profits (DRDID Results)

	(1) Full sample	(2) Dabi	(3) Progoti
ATET	0.105**	0.036	0.253**
	(0.051)	(0.055)	(0.102)
Covariates	Yes	Yes	Yes
N	21,472	13,498	7,974

Note: Figures in parentheses are standard errors. The dependent variable here is the inverse hyperbolic sine transformed value of the profit amount (in BDT).
∗ p < 0.10, ∗∗ p < 0.05, ∗∗∗ p < 0.01

Table 10: Impact on Food Expenditures (DRDID Results)

	(1) Full sample	(2) Dabi	(3) Progoti
ATET	0.009**	0.008	0.013*
	(0.004)	(0.006)	(0.007)
Covariates	Yes	Yes	Yes
N	21,472	13,498	7,974

Note: Figures in parentheses are standard errors. The dependent variable here is the logarithm of per capita food expenditure (in BDT).
∗ p < 0.10, ∗∗ p < 0.05, ∗∗∗ p < 0.01

Table 11: Impact on Food Security (DRDID Results)

	(1) Full sample	(2) Dabi	(3) Progoti
ATET	-0.117***	-0.078*	-0.205***
	(0.037)	(0.048)	(0.056)
Covariates	Yes	Yes	Yes
N	21,472	13,498	7,974

Note: Figures in parentheses are standard errors. The dependent variable here is an indicator variable of whether the household had to consume a lower-than-usual amount of food due to poverty.
∗ p < 0.10, ∗∗ p < 0.05, ∗∗∗ p < 0.01

7. Conclusion

Microfinance can facilitate significant improvements in household welfare by alleviating liquidity constraints. In this paper, we estimate the impact of microfinance on household welfare during the crises induced by the COVID-19 pandemic. Employing a DID methodology and comparing borrowers who received microloans after the outbreak of the pandemic with borrowers who did not, we find that access to microloans is associated with significantly increasing business profits, food expenditure, and food security. Among *Progoti* borrowers, the results indicate a significant impact on business earnings for male borrowers, while the impact on this indicator is insignificant for female borrowers. However, female *Progoti* borrowers experience a significant positive impact on food expenditure. Hence, it appears that among *Progoti* borrowers, the male borrowers tend to spend the loaned money more effectively to increase business earnings, while female borrowers focus on spending the money on subsistence needs. Future research focusing on identifying the mechanisms behind these could shed further light on disentangling the issue.

Our results thus have policy relevance, both with regard to the impact of microloans during COVID-19, as well as the impact of credit during a shock. Although we cannot speak to the external validity of our research, having access to microcredit during an emergency could help poor households weather such crises better.

One critical avenue for future work would be to understand how persistent these effects are. Our research was conducted less than a year after the emergence of COVID-19 and the subsequent lockdowns, with results indicative of *Progoti* borrowers who lacked microloans still lagging behind. Do these borrowers drop out of the credit market and fall into a poverty trap? Or

does financial inclusion lead them towards a path of convergence? How path-dependent is the tumult caused by COVID-19 on households and the credit market? Further research on these issues would yield valuable insights.

Notes

[i] Microcredit Regulatory Authority. (2018). *NGO-MFI in Bangladesh, 2014, 2015, 2016, 2017 & 2018 (various issues)*. http://www.mra.gov.bd/

[ii] We provide more details on these products in the next section.

[iii] Source: https://www.brac.net/program/microfinance/

[iv] The description is based on the information available at: www.brac.net/sites/default/files/microfinance.pdf, https://www.brac.net/program/microfinance/ & www.brac.net/images/factsheet/MF_Briefing_Doc_English.pdf

[v] Rainfall data are collected from the Bangladesh Bureau of Statistics, Ministry of Planning, Government of Bangladesh. BBS reports rainfall data for 34 weather stations scattered across the country. We have matched our survey branch office with the nearest weather station.

[vi] MIS data show that 90% of the male borrowers took loans for business purposes, while more than 40% of the female borrowers took loans for migration purposes.

[vii] The DID results presented in sections 6.1 to 6.5 use data on 10,794 households, while the DRDID results use data on 10,736 households because data on demographic characteristics of 58 household heads were not available.

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Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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Appendix

Table A1: Characteristics of Intended Sample and Actual Sample

Variable	Successful survey (Attrition= 0) (1)	Unsuccessful survey (Attrition =1) (2)	Difference (successful vs unsuccessful) (3=1-2)
Panel A: Dabi			
Principal amount (BDT)	47,765.49	48,024.73	-259.2326
	(403.79)	(375.904)	(557.946)
Installment amount (BDT)	4,537.31	4,562.393	-25.08305
	(38.363)	(35.711)	(53.007)
Respondent's age (years)	35.334	35.572	-0.237
	(0.116)	(0.107)	(0.159)
Respondent male	0.008	0.005	0.002*
	(0.001)	(0.000)	(0.001)
N	6,793	9,140	

Panel B: Progoti			
Principal amount (BDT)	237,308.2	234,555.5	2,752.69
	(3,111.316)	(3,207.501)	(4,526.79)
Installment amount (BDT)	22,463.8	22,209.43	254.3709
	(290.5158)	(299.783)	(422.840)
Respondent's age (years)	40.404	39.274	1.130***
	(0.158)	(0.189)	(0.245)
Respondent male	0.730	0.636	0.094***
	(0.007)	(0.009)	(0.011)
N	4,001	3,082	

*Note: Figures in the parentheses are standard errors. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.*

Table A2: Heterogeneity of Effects with Respect to Treatment Timing

	Dabi			Progoti			Full sample		
	(1) Business profit	(2) Food expenditure	(3) Food security	(4) Business profit	(5) Food expenditure	(6) Food security	(7) Business profit	(8) Food expenditure	(9) Food security
Effect for early loan takers	0.041	0.014	-0.006	0.126	0.016	-0.052***	0.100	0.013	-0.015
	(0.146)	(0.015)	(0.015)	(0.240)	(0.022)	(0.018)	(0.130)	(0.013)	(0.012)
Effect for late loan takers	0.033	0.009	-0.0064	0.098	0.008	-0.017	0.064	0.008	-0.009
	(0.139)	(0.014)	(0.0147)	(0.213)	(0.019)	(0.016)	(0.121)	(0.012)	(0.011)
P-value on the equality of two impacts	0.959	0.781	0.062	0.915	0.722	0.011	0.757	0.794	0.031
Constant	2.645***	7.379***	0.132***	4.851***	7.554***	0.076***	3.486***	7.446***	0.111***
	(0.079)	(0.008)	(0.008)	(0.118)	(0.010)	(0.009)	(0.068)	(0.006)	(0.006)
Number of observations	33,965	27,172	40,751	20,005	16,004	24,001	53,970	43,176	64,752
R-squared	0.006	0.008	0.047	0.023	0.003	0.027	0.010	0.003	0.037

*Note: Figures in the parentheses are standard errors. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. We control individual and time-fixed effects, rainfall and a dummy for early loan takers*

Figure F1: The Number of Borrowers Each Year as a Percentage of Total Borrowers (*Dabi* Sample; N=6,793)

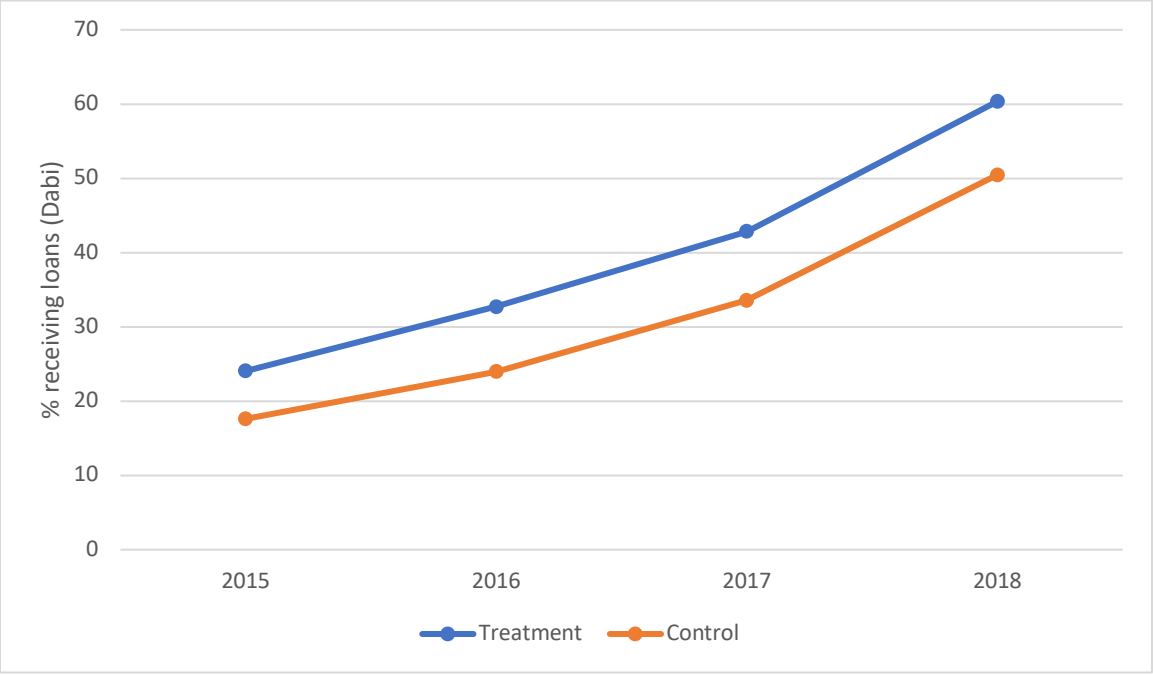


Figure F2: The Number of Borrowers Each Year as a Percentage of Total Borrowers (*Progoti* Sample; N=4,001)

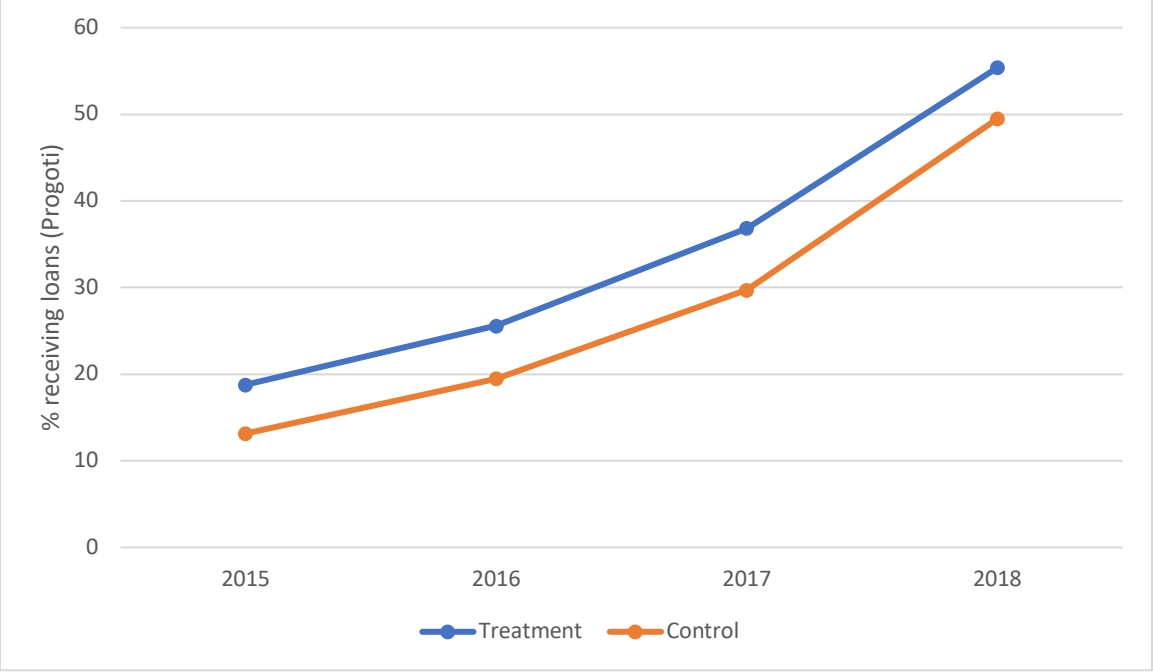


Figure F3: The Number of New Borrowers Each Year as a Percentage of Total Borrowers (*Dabi* Sample; N=6,793)

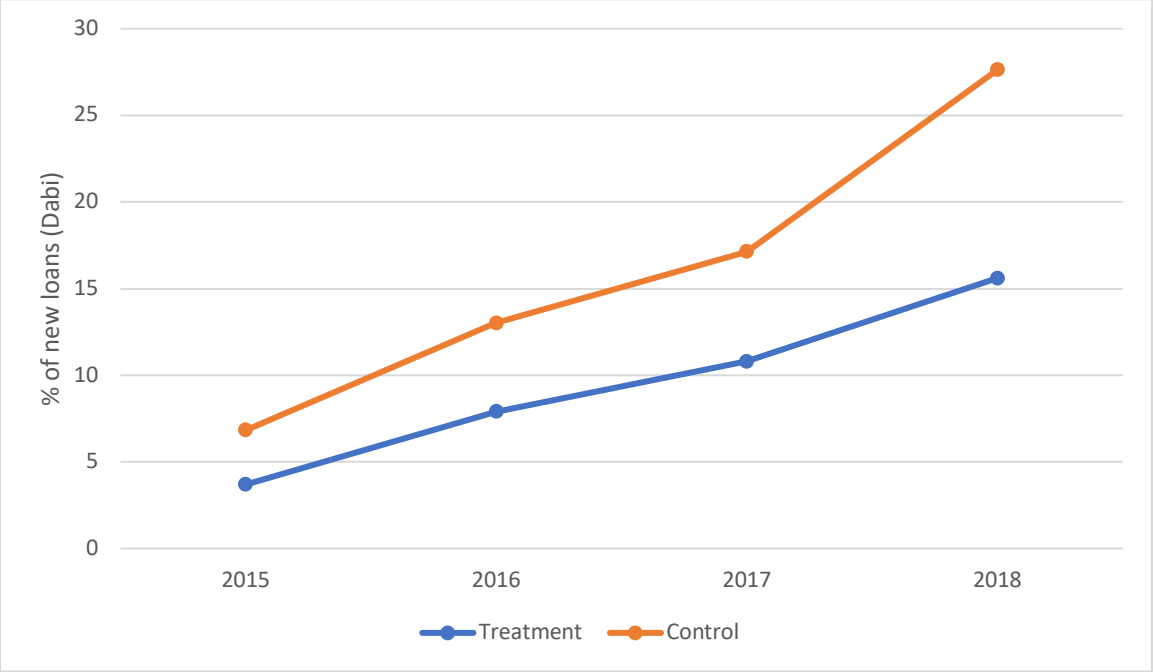


Figure F4: The Number of New Borrowers Each Year as a Percentage of Total Borrowers (*Progoti* Sample; N=4,001)

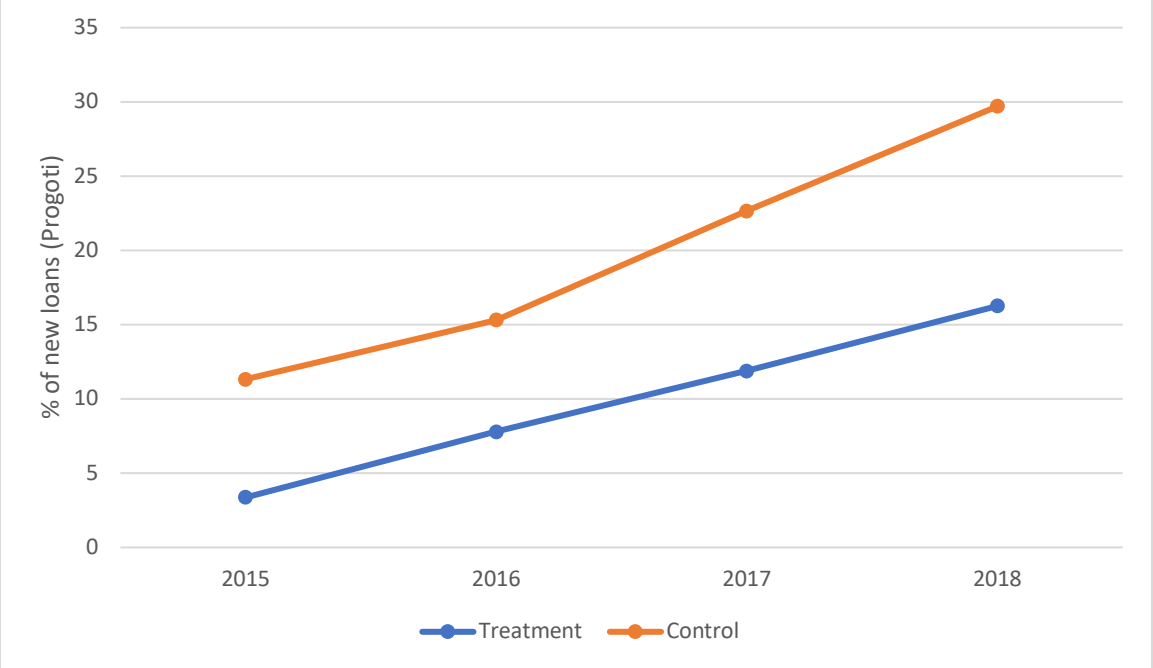
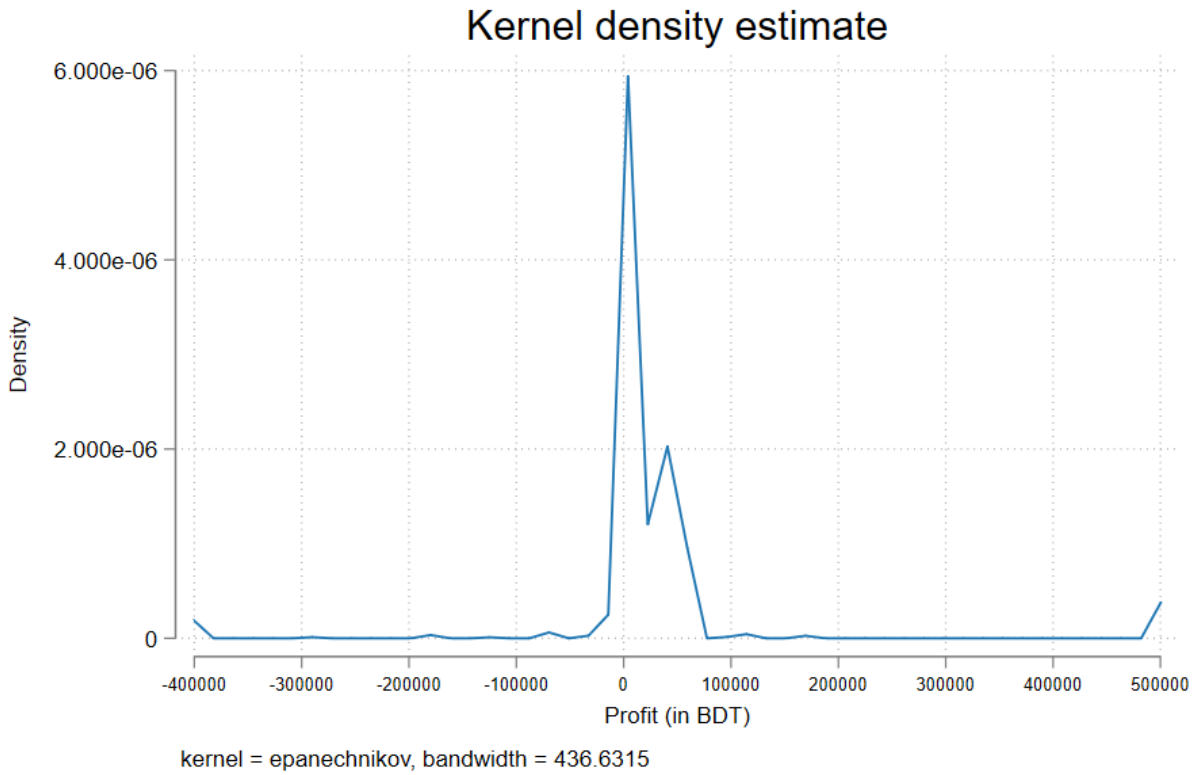


Figure F5: Distribution of Business Profit



Note: Values greater than 500,000 are represented as 500,000 (0.03% observations), values less than -400,000 are represented as -400,000 (0.03% observations)