International Journal of Development and Conflict
12(2022) 22–47

IMPACT OF COVID 19 ON BORROWINGS FROM SELF-HELP GROUPS AND OTHER SOURCES OF MICROFINANCE

NISHI MALHOTRA
Ph.D. Scholar, IIM Kozhikode

DR. PANKAJ KUMAR BAAG
Assistant Professor, Finance, Accounting & Control
IIM Kozhikode

COVID 19 is a pandemic that has emerged as a major crisis for the entire world. With the emergence of COVID 19, the borrowing pattern of individuals have changed drastically. During the second phase of COVID 19, the Government has imposed severe restrictions in terms of the Work from Home and Social distancing. This led to a decline in borrowing, particularly from the Self-help groups. This study seeks to establish the relationship between borrowings and Lockdown. Further, the study seeks to measure the gendered impact of COVID 19 on borrowings from different sources. The Difference in Difference method & Kernel based PSM (Propensity Score Matching) was used to identify the impact of COVID region (Rural Vs Urban) and the gendered impact of COVID 19 on the borrowings from different sources of microfinance. The results establish that during the COVID 19 period, the Rural regions witnessed a decline, whereas the borrowings from the bank and nonbanking finance companies increased drastically.

Keywords: Self-help group, Microfinance, Household Borrowings, Lockdown

1. Introduction

COVID 19 pandemic came as a catastrophe for the entire human community and it threatened the sustainability and livelihood of the majority of the population living below the poverty line. The mandated social distancing and restrictions on movement through lockdown adversely impacted the livelihoods of the marginalized poor at the bottom of the pyramid. CMIE Consumer pyramid data reveals that the COVID 19 pandemic led to a vast reduction in economic activities the risk of the solvency of the microenterprises became a reality. The lockdowns in the year 2020 due to the national pandemic necessitated due to the pandemic COVID 19 led to the closure of most of the enterprises. In May 2020 after the announcement of the Lockdown, MFIs faced immense solvency challenges as the small businesses in the unorganized sector were affected by liquidity crunch and no reserves. This

*Email: nishim13fpm@iimk.ac.in

further accentuated the financial exclusion of the poor and increased their vulnerability to moneylenders and other informal sources of finance. During the pandemic due to lack of regular source of Income, the non-repayment of loans and moral hazard were the major risks facing the microfinance entities like Self-help groups, (Chakma, 2020). Despite all challenges, the unique institutional governance structure of these self-help groups based on social capital and trust became the driving force behind the success of these groups in promoting social welfare, manufacturing, and delivery of essential commodities and support to the victims of COVID 19. Recognizing the potential of this initiative, the Government of India extended the financial support and credit to this landmark community initiative, the self-help group linkage program to promote social and economic welfare. In March 2020, in the months to the follow up of Lockdown, the Government of India provided sops to the Microenterprises through the Self-help groups, (Sudip Bandyopadhyay, 2021). As a consequence, the self-help groups enhanced the outreach of microfinance to the poor. This study aims at evaluating the impact of Microfinance initiatives such as Self-help groups on the operational sustainability and profitability of Microenterprises. During a pandemic, most NGOs that initially assisted rural community groups and self-help groups were unable to assist them. SHGs faced operational sustainability issues such as inability to gather, convene, and save, (Sangwan et al.). Despite all the physical challenges posed by the pandemic COVID 19, the SHGs through the social capital enhanced the collaboration and enabled these women groups to meet the challenges, (P. Christian, 2019). With their collaborative, inclusive, democratic, and participative governance structure, SHGs emerged as a panacea to all the financial ills and problems posed by COVID 19, ((Desai & Joshi, 2013).; Kumar et. al. 2019 & Reddy & Manak, 2005). During this period, the Indian government provided much-needed support to rural enterprises through self-help groups and easy credit. The Indian government recently announced a USD 270.42 billion packages to support the rural manufacturing sector under the recently launched "Atamanirbhar Bharat" scheme, (The Government of India, 2020). The Indian government increased the limit of collateral-free loans under the Deen Dayal National Livelihood Mission to USD 27,041. The "Garib Kalyan Yojana" announced a special package of USD 23.66 billion for the poor during the pandemic. Self-help groups benefited from livelihood initiatives like Atamanirbhar Nidhi, (PM SvaNidhi). The street vendors were given a USD 135.21 loan under this scheme. Under the Pradhan Mantri Jan Dhan Yojana, all female members received an extra USD 6.76, (The Government of India, 2020).

National Agriculture and Rural Development Bank gave a push to these entities through credit support and federating. Most of the state governments extended the national employment schemes under MNREGA and Jeevika to these groups, in order to facilitate the engagement of these self-help groups in the community initiatives. Despite huge levels of unemployment reported during this pandemic, the SHG leaders were involved in the community development activities, (UNICEF, 2020). In fact, the self-help groups emerged as the pivot in mitigating the negative impact of COVID 19. The Indian government announced a Rs 20 lakh collateral-free loan for the poor. The Ministry of Finance provided Rs 1.70 lakh in relief to the poor and vulnerable under the Pradhan Mantri Gareeb Kalyan Yojana. 63 lakh self-help groups supporting 7 crore families received immediate financial assistance (Times of India, March 2020). These self-help groups emerged as a community-sensitive vehicle to create awareness among the villagers and supported the nation by manufacturing masks and sanitizers. In the wake of the COVID 19 pandemic, there are no empirical studies evaluating the impact of SHGs on household economic welfare. The pandemic raised questions about the financial and social sustainability of Indian Self-help groups, but they also helped to improve the economic and social welfare of the poor during the pandemic. During COVID 19, this study will assess the impact of Self-Help Groups on marginalised groups' Income.

2. Literature Review

"Going beyond money, monetary relations, and private property is one way to defy the capitalist law of value" (Nelson, A, 2016). They have become a model of local economies, self-organization, direct democracy and autonomy. These organisations have emerged as a panacea to the economic woes of those at the bottom of the pyramid who lack access to financial services (Liegey, 2020**).** COVID 19 has become a pandemic and a global health issue affecting all nations, (Susilawati et al.) COVID 19 was declared a pandemic on March 11, 2020. The lockdown policy adopted by most countries worldwide puts pressure on economic activities. As the pandemic hit the economy, the small entrepreneurs' micro-businesses ceased to be viable and profitable (Malik, 2020). Microfinance clients defaulted on loans, compounding their repayment issues. The pandemic caused a liquidity and capital crunch for microfinance companies. Despite all the arguments, the literature shows that microfinance helped reduce Poverty and empowered the poor (Roodman, 2014). Microfinance became the baton to overcome the darkness of this pandemic for the women entrepreneurs who are funded by Self-help groups. Microfinance programmes aim to help the poor and marginalized. This initiative helped women access loans without physical collateral by leveraging social capital, trusts, and relationships (Maclean, 2010). For the marginalised poor, access to capital meant financial inclusion, which augmented personal Income and led to economic empowerment (Murshid, 2020). (Kumar, 2005) claims that microfinance can help mitigate pandemic effects by increasing income sources. Many of the researchers highlight that the landmark model of microfinance in form of group lending is a paradigm shift in individual liability loans and facilitates access to a loan for the people at the bottom of the pyramid, (Counts, A., 2008). The extant literature do mentions the challenges in operational sustainability of these groups due to the imposition of the lockdown and various restrictions such as work from home and social distancing. Yet, different research studies highlight that group lending has helped to improve the economic welfare if the members of the groups. In another major development. (Arunachalam & Crentsil, 2021) highlighted that the microfinance initiative such as the Joint Liability group of the self-help group have highlighted that the rural regions have fared much better in terms of generation of Income and adherence to the social protocols and restrictions. rural regions are able to better handle all the crises due to the wide-open spaces and clean villages. Most of the Self-help groups, MFIs (Microfinance Institutions), NBFC (Non-Banking Finance Companies) having presence in the rural regions can provide access to credit to the poor people. Due to the lower density of population. The members of the community will be at far lesser risk of the pandemic as compared to their urban counterparts. While the existing literature highlights the importance of microfinance, it also highlights that there is extremely less gender difference in access and utilization of loans among the marginalized poor. And the repayment of loans is largely determined by the information asymmetry, output, and Income. In the face of a pandemic due to the declining output, the Income of the enterprises has declined but the Joint Liability Groups provide its member the much-needed credit and skill-building support. In the wake of the pandemic various social welfare schemes such as MNREGA, PMJDY have given the required push and propelled the credit support, which provided the much-needed economic impetus and support to the economic activities of the small business houses. Thus, there is no doubt that microfinance during COVID 19 plays an extremely important role in the promotion of financial inclusion. The major objective of this study is to measure the impact of microfinance on the economic welfare of the borrower. Various PSM studies show that microfinance initiatives increase poor households' Income. One of the major developments in microfinance during a pandemic is that it has challenged existing government regulations. During the pandemic, the importance of government programs like microcredit and direct benefit transfers has increased. The Government of India has introduced various schemes such as the MNREGA, PMJDY, etc which have increased the financial sustainability of the Joint Liability Groups or the Self-Help Groups. Microcredit has helped the borrowers to smoothen their consumption and also increased their financial sustainability, (Observatory, 2020). During the pandemic due to the dwindling economic profits, the formal financial institutions are wary to lend to the poor due to the lack of physical collateral and undertaking. In this scenario, the self-help groups through their self-regulating structure could provide much-needed support to the micro-enterprises. Since the self-help groups operate on the principle of personal affiliation, they could provide loans to the members-only on basis of trust without any need for physical collateral. Earlier studies have highlighted that the various factors including age, education, family type, and distance from the market have a significant impact on the participation of women in Self-help groups, (Joshi, 2019). This study aims at analyzing the impact of Self-help groups during COVID 19 and after COVID 19 in promoting the economic welfare of the household through the increase in income of the household. Through the extant literature, there is no study in this domain and only a few studies exist that discuss the impact of Microfinance in combating COVID 19 but there is no study that discusses the impact of community and democratic initiatives like Self-help groups on Income and economic welfare of the households.

(Coate, 2013) in his research study has highlighted that the group lending initiatives by use of the social collateral mitigate the problem of moral hazard or issues in loan repayment. As per the author in a joint liability group, all members know each other, and if even one of the member's defaults on the loan all other members repay back the loan. They have personal information about each other and this helps in reducing the information asymmetry. In case of repeated default, the members by virtue of social networks impose social sanctions on the members of the group. During the time of a pandemic like COVID 19, the members face the threat of moral hazard and delay in repayment of loans (Townsend et.al , 2003) in their research paper has highlighted that in case of the default in the repayment of loans the formal financial institutions impose a penalty for the non-repayment of loans, and the other members of the group peer monitor and through Joint liability are responsible for the repayment of the entire loan. According to another famous study, (Niels Hermes, 2005) in their research study have highlighted that in a group due to the joint liability members do peer monitor each other they jointly invest in selection, screening, and monitoring of the financial activities of the group. This helps to reduce the risk of Moral Hazard and Peer Monitoring. In a pandemic scenario like COVID 19, the Joint liability group according to us provides protection against moral hazard and adverse selection. Though with restrictions on meeting and social distancing, the operations of SHGs have stopped and there is a sudden decline in the savings of the groups, in a pandemic situation by virtue of social collateral, particularly in rural India, the SHGs have been instrumental in promoting the economic welfare of the borrowers.

3. Research Problem

This study seeks to measure the impact of the microfinance in form of borrowings from the Self-help group on the economic welfare or the average Income of the household during COVID 19 using the Propensity Score Matching method. It also aims to calculate the probability of borrowing from the different sources using the Difference in Difference method using the Panel data. This analysis is done using the CMIE Consumer Pyramid survey data for the period May to August 2019 & May to August 2021.The baseline data of May to August 2019 is the control group and the data from May to August 2021 is the treatment group. This is the data for the 4 months. The data for May to August, 2019 serves as the baseline survey. Using DiD design this study aims to measure the impact of the intervention on the economic welfare in the sample.

RQ: COVID 19 does not impact the borrowings from the different sources such as SHGs, Banks, MFIs, NBFC, Shops and Moneylenders?

4. Methodology

This research study aims to assess the impact of microfinance through self-help groups on the financial sustainability of borrowers. In the data that we have collected from the CMIE Consumer Pyramids, it is not possible to preselect the control group. These surveys present the panel data, which are representative of the national, rural and urban levels. Out of the entire survey, we have selected entire dataset of household for the purpose of analysis. In this paper we have used the Difference in Difference regression to estimate the casual effect through the analysis of the Panel data. In the 4-month data that we have taken from the Wave 19 of the Consumer Pyramids dataset is unbalanced at the baseline and the endline. We have assumed the Pre Covid period from May 2020 and June 2020 as the Pre-treatment data and the data for March 2021 and April 2021 is the Post treatment dataset. This dataset has an issue of time invariant differences between the Treatment and the control group as the control and treatment groups are not homogenous.

Research problem 1: Is gender an important consideration in providing credit through various formal and informal channels?

Kabeer has defined women empowerment as the process by which women challenge existing norms and culture. This research question aims to answer the question that how does the microfinance leads to greater empowerment? The study presumes that greater economic independence leads to the women empowerment, (Rehman, H., Moazzam, D. A., & Ansari, N., 2020). In this study we intend to investigate how much is gender important in ensuring access to credit from different sources including the Self-help groups. Bank, Microfinance, Nonbanking finance companies, shops and moneylender. Within the feminist paradigm, (Mayoux, 1999) highlights that empowerment is the process of internal revolution and power within, power to through enhanced capabilities. It is the process of enhancing the capabilities of the women to participate in various decision-making processes. (Duflo, 2012) highlight that that women empowerment can lead to economic empowerment. Financial programs that are focussed on women help in bridging the gap between the men and women in achieving the access to finance, (Muravyev, A., Talavera, O., & Schäfer, D., 2009, Anderson, 2020) COVID 19 emerged as a pandemic and there was increasing inequality between the men and the women. Using the sample of 1.4 lakh households that are comprised of the small/marginal farmers and the entrepreneurs, we found that gender bias is no longer an important factor in providing the access to finance through various sources. (S. Marlow, 2005) argue that the availability and access to finance is an important factor in development of an enterprise. Often women face higher bias in access to finance then their male counterparts. (Treichel, 2006) report that the refusal in granting credit is higher for females in banks.

Description of variables

Our database comprises of CMIE CPHS (Consumer Pyramid Household) database. For analysis, we selected the pre-treatment Control group as households surveyed from May 2019 to August 2019. And the post-treatment "Treatment" group is the period, May 2021 to August 2021, which is the period of extreme lockout and COVID 19 restrictions. A panel of 1,41,454 households was created for these two periods.

Household Gender

In our model, there are 1,11,390 households dominated by women and 30,064 households dominated by men or have equal numbers of men and women. In this study, we used the CMIE CPHS database, the most prominent representative dataset of the Indian diaspora. In most studies, the female or male head of household is considered an explanatory variable. Women reside in homes where the family is a male member. In CPHS data, the distribution of households as male and female is taken to represent household characteristics better to explain its behavior in terms of Income, expenditure, and borrowing patterns (Consumer Pyramids Household Survey, 2020).

Covid

Covid refers to the period of pandemics during which the world globally suffered the brunt of the COVID disease. We have taken the second period, May to August 2021, as the treatment period or period of COVID 19 and severe Lockdown. And the period of May to August 2019 is the period before the COVID 19 pandemic.

Poverty

Poverty Score as an independent variable

Microfinance is an essential tool for the reduction of Poverty, (C Henry , 2003). Microfinance is aimed at people below the poverty line. These people who do not have enough collateral and regular source of Income get access to money, which helps them reduce Poverty. Microfinance helps people in institution building and reduces disparity among poor people. Microfinance Assessment Tool aims to increase the transparency on the outreach of the microfinance institutions to integrate poverty focus; This tool is based on the Principal Component Analysis to create an index of Poverty to measure the level of Poverty among the poor people. In this regard, we have used the CMIE Consumer Pyramid database, the Aspiration dx survey, and the list of questions that are included in the questionnaire include:

1. How many household members are there in the family?

   Points and ranking for this question are given as follows:
   - Eight or Move
   - Seven
   - Six
   - Five
   - Four
   - Three
   - Two
   - One

2. What is the general education level of the members of the group?
   - Primary or below or not literate
   - Middle
   - Secondary or higher
   - No female head/Spouse

3. Does the household possess a refrigerator?
   - No
   - Yes

4. Does the household possess a washing machine?
   - Yes
   - No

5. Does the household possess a television?
   - Yes
   - No
6. 6. Does the household possess the Cooler?
   - Yes
   - No
7. Does the household possess a regular supply of water?
   - Yes
   - No
8. Does the household possess a regular supply of power?
   - Yes
   - No
9. Does the household possess a motorcycle, scooter, car, or jeep?
   - Yes
   - No
10. Does the household possess a GENSET?
    - Yes
    - No

Using this tool, we improvised our data. We added additional data about the basic amenities available with the respondents in the form of regular water supply, power supply, access to TV, access to a washing machine, access to Genset, car. The data was calculated with the scoring mechanism mentioned above, and scores were populated. These scores for both the cycles were used to assess the impact of Poverty on access to microfinance. In the earlier approach to microfinance, Rhyne (2000) suggests that Microfinance aids in reducing the inequalities among poor people.

Rural Region as an independent variable and source of difference – Rural finance targets the poorest of the poor. This social class lacks collateral and cannot organize (Seibel & Parhusip, 1990). These people needed subsidized credit, and Microfinance became the panacea for the poor in rural India. Because microfinance aims to Reduce Poverty, we chose poverty shock or change in poverty index during COVID 19 as a factor impacting self-help group borrowings. Public policy initiatives in microfinance helped increase rural outreach and credit volume (Burgess and Pande, 2005). We used the pandemic to borrow from non-formal institutions like self-help groups. SHGs are a microfinance intervention for the poor. The big banks shied away from serving them to reach the poor due to mission drift (Burgess & Pande, 1990). We hypothesize that changes in poverty score reflect self-help group borrowing propensity changes. Lockdown and social distancing restrictions exacerbate this issue. The treatment period is May to August 2021, and the control period is May to August 2019. In addition, the Poverty Score, (C Henry , 2003) will help assess the impact of changing asset ownership on obtaining more loans through Self-help groups.

- Does the household possess a refrigerator?
- Does the household have a washing machine?
- Does the household possess a television?
- Does the household possess a cooler?
- Does the household have a regular supply of water?
- Does the household have a regular supply of electricity in the house?
- Does the household possess a motorcycle, scooter, motor car, or jeep?

The poverty score is derived from the asset score data. This score includes data on the number of houses, refrigerators, coolers, washing machines, televisions, computers, cars, generators, tractors, cattle owned, and access to power and electricity. A toilet is the final data point. Each asset starts equal. We calculated the poverty shock as the difference in asset ownership between the Control and Treatment periods.

Poverty Score = (∑Houses owned + Refrigerators + Air conditioner + Coolers + Washing machine + television + computer + cars owned + two wheelers + genset + tractors + cattle + Power + Water + Toilet)

Income of household
Income Pyramid$_{dx}$ provides the time series of the Income of the household and its composition. In this study, we have taken the total Income of the respondent from all the sources, including wage and pension earned by members, dividends earned, interest on saving and interest, provident fund and insurance, and Income from property and other sources as the proxy for the Income of household. Data for the borrowing habits are taken from the Consumption$_{dx}$ Pyramids. Regarding the families' Income, the data is taken from the Income$_{dx}$ Pyramid. In the Consumption dx Pyramid, the information is collected in a cycle of 4 months. From the income dx, the data is calculated and averaged over the period. This average Income is further transformed by taking the log of the Income.

Education
The education of the household refers to the essential qualification that a person has acquired. In the CMIE CPHS Survey, the composite classification for the family is calculated based on the education level of the members. In a household, the highest level of sort, whether it is Graduation, Matriculate or literacy, or illiteracy, determines the level of education of the family. In our study, we have used the binary classification of 0 for illiterate households (No members who can read and write) and others as members who can read and write.

Interaction term or Difference in Difference
The interaction term between the household gender and covid denotes the difference in the difference variable. This variable reflects the difference between the male and female-dominated households during the COVID 19 in determining the access to different forms of microfinance, i.e., microfinance from the Self-help groups, banks, Microfinance institutions, nonbanking finance companies, Shops, and Moneylenders.

Migration

Migration is the data in CMIE CPHS that has become available from the period 2021. This data provides information about whether the family has shifted from the state of domicile or not. This is a binary variable that takes value 1 for the member who has emigrated and 0 for the member who has not emigrated.

Empirical Strategy

We have used the Consumer Pyramid Household Survey data from May Aug 2019, as the baseline control group and May-August 2021 as the ending control group. The overall change in the borrowing pattern of the individuals due to the pandemic is estimated using the following equation

$$Y_{ict} = \alpha 0 + \beta_1 (Lockdown_{mt}\ X\ Year_{2020}) + \beta_{2.}\ Lockdown_{mt} + + D_i + Year_{2020} + \varepsilon_{ict}$$

Y_{ict} is a dummy variable that takes the value of 1 if the individual household *i* borrowed from the specific financing source *c* at time *t* and 0 otherwise. Lockdown is a binary variable with a value of 1 for the period May-August 2019 and 0 for the period May-August 2021. β_1 reflects the changes in the borrowing pattern in the Lockdown period. The year $_{2020}$ is an indicator value that takes value one if the period is the Year 2020 and 0 otherwise. The above strategy is akin to the difference in differences strategy where β_1 gives the change in borrowing due to the Lockdown in the year 2020 compared to the non-pandemic period in May to August 2019 after accounting. This Lockdown is interacted with the COVID 19 period to calculate the change in Income due to the Lockdown. After this, we have done the Hetrodeskecity tests taking the differences between the Females and Males and Rural Region area during the COVID 19 on the borrowing patterns of the households.

Change in Borrowing pattern due to COVID 19 in the second wave of Lockdown

Table 1. Impact of COVID 19 & Lockdown on Borrowing Patter

VARI-ABLES	(1) SHG	(2) Bank	(3) MFI	(4) NBFC	(5) Shops	(6) Money-lender
Lock-down2.0. $Post_{20}$	0.160***	-0.0187	0.0193	-0.00551	-0.0638***	0.229***
	(0.0555)	(0.0323)	(0.156)	(0.0473)	(0.0228)	(0.0699)
Covid	-0.407***	-0.904***	-0.924***	-0.319***	-0.290***	-1.654***
	(0.0557)	(0.0274)	(0.144)	(0.0421)	(0.0217)	(0.0679)
Education	0.712***	0.540***	0.814***	0.219***	1.006***	0.579***
	(0.0791)	(0.0500)	(0.245)	(0.0757)	(0.0351)	(0.108)
Occupation	-0.526**	-0.0560	-1.292	0.907**	-0.967***	0.240
	(0.238)	(0.197)	(1.042)	(0.459)	(0.117)	(0.255)

(*Contd.*)

VARI-ABLES	(1) SHG	(2) Bank	(3) MFI	(4) NBFC	(5) Shops	(6) Money-lender
Migration	0.969***	1.081***		0.502***	0.499***	0.487***
	(0.0466)	(0.0288)		(0.0419)	(0.0208)	(0.0612)
Gender	0.0201	-0.0852	0.487***	-0.324	-0.00715	0.116
	(0.771)	(0.601)	(0.137)	(1.415)	(0.243)	(1.546)
Score	-0.00891***	0.00130	-0.0156***	0.00686***	0.000933	0.00168
	(0.00213)	(0.00106)	(0.00585)	(0.00166)	(0.000823)	(0.00256)
Observations	12,984	42,566	2,020	14,938	68,928	11,656
Number of HH_id	6,492	21,283	1,010	7,469	34,464	5,828

Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p<0.1

Table 2. Heterogeneity Tests - Change in Borrowing pattern due to COVID 19 in the second

Variables	SHG	Bank	MFI	NBFC	Shops	Moneylender
Rural. Covid	-0.749***	0.461***	-0.327*	0.274***	0.209***	-0.664***
	(0.0587)	(0.0332)	(0.176)	(0.0535)	(0.0233)	(0.0766)
Covid	-0.0659	-1.074***	-0.836***	-0.384***	-0.393***	-1.333***
	(0.0507)	(0.0250)	(0.124)	(0.0368)	(0.0196)	(0.0588)
Gender	0.686***	0.543***	0.834***	0.235****	1.011***	0.562***
	(0.0798)	(0.0502)	(0.247)	(0.0759)	(0.0351)	(0.108)
Education	-0.608**	-0.0958	-1.290	0.895*	-1.008***	0.259
	(0.246)	(0.195)	(1.041)	(0.459)	(0.117)	(0.266)
Occupation	0.901***	1.109***	0.508***	0.510***	0.503***	0.471***
	(0.0473)	*(0.0290)	(0.137)	(0.0420)	(0.0208)	(0.0615)
Migration	0.168	-0.127	-	-0.322	-0.0379	0.0769
	(0.756)	(0.602)		(1.415)	(0.244)	(1.835)
Score	-0.00770***	-0.000837	-0.0144**	0.00612***	0.000216	0.00365
	(0.00215)	(0.00108))	(0.00583))	(0.00137))	(0.000828)	(0.00256)
Observations	12,984	42.566	2,020	14,938	68,928	11,656
Number of HH_id	6,492	21,283	1,010	7,469	34,464	5,828

Standard errors in parentheses
***p < 0.01; **p < 0.05 ; p < 0.1

One of the major factors responsible for the lack of Microfinance is that many banks are wary of lending to the poor. During the pandemic phase, the banks in India have started providing various moratorium repayment and collateral-free loans to the poor (M Yunus, 2003). Microfinance is meant to provide access to finance to the poor people excluded from the financial system, but there is no such evidence in the data (Hashemi, 1996). With the change in the rural finance policies, gender is no longer a significant factor that impacts access to finance. However, (Morduch, 1999) highlights the disparity between female-dominated households and male-dominated households regarding access to finance. Formal financial institutions exhibit microfinance schism and are wary of lending to poor people. Within the welfarist approach, the banks in rural regions are pushed to provide credit to indigent clients during pandemics. From the analysis of data, it becomes apparent that banks successfully give loans to the poor members in the Rural region. Credit formation through Self-help groups has been impacted. In approximately 87% of the districts, the SHG borrowings have been adversely affected (NABARD Department of Economic Analysis, 2020). In the case of SHG, the ability to conduct timely meetings has been impacted adversely, and this is affecting.

Similarly, MFI operations have been adversely impacted in the country across different states and districts. During the second wave of COVID 19, the state governments introduced various measures such as the loan waiver of the members of the self-help groups. In Tamil Nadu, the Government promised to waive off the loans of the people in default of loans

Table 3. Heterogeneity Tests - Gendered Impact of COVID 19 on Borrowing patterns among the household

Variables	**Model SHG (1)**	**Model Bank (2)**	**Model MFI (3)**	**Model NBFC (4)**	**Model Shops (5)**	**Model (6)**
Gender *Covid	0.498*** (0.0758)	0.364*** (0.0449)	0.252 (0.198)	0.347*** (0.0648)	0.492*** (0.0309)	0.409*** (0.0893)
Covid	-0.416 (0.0490)	-0.979*** (0.0233)	-0.836*** (0.124)	-0.384*** (0.0368)	-0.393*** (0.0196)	-1.333*** (0.0588)
Gender	0.528*** (0.0831)	0.398*** (0.0521)	0.834*** (0.247)	0.235**** (0.0759)	1.011*** (0.0351)	0.562*** (0.108)
Occupation	0.954*** (0.0467)	1.069*** (0.0289)	0.488*** (0.137)	0.500*** (0.0420)	0.482*** (0.0209)	0.477*** (0.0614)
Education	-0.485** (0.239)	-0.0385 (0.197)	-1.265 (1.042)	0.887* (0.461)	-0.975*** (0.117)	0.262 (0.255)
Migration	-0.0318 (0.772)	-0.185 (0.598)	-	-0.323 (1.415)	0.00545 (0.244)	0.0601 (1.612)
Score	- 0.00897*** (0.00214)	0.00114 (0.00106)	-0.0157*** (0.00585)	0.00666*** (0.00166)	0.000741 (0.000828)	0.00134 (0.00257)
Observations	12,984	42.566	2,020	14,938	68,928	11,656
Number of HH_id	6,492	21,283	1,010	7,469	34,464	5,828

Standard errors in parentheses
***p < 0.01; **p < 0.05 ; p < 0.1

Gendered Impact

This research paper analyses the gendered impact of COVID 19 on the borrowing habits of the borrowers. Indian Government has adopted the UN Sustainable Development Goal to reduce Poverty. The Government of India has introduced various sops and incentives for the poor, including grants, subsidies, etc. The context of the COVID 19 pandemic has led to immense pressures on the entrepreneurs, but there is no literature on the financial difficulties faced by women entrepreneurs during the period. During the COVID 19 period, many small businesses, including the street vendors, small shops, and many others, we're dependent on cash and faced severe challenges. From the data analysis, there still exists a gender gap between females and males in terms of access to finance. As compared to women, men have a higher propensity to borrow from different sources of finance. The Government of India introduced various schemes that gave a push to microfinance loans. The Government of India introduced a mortarium of loan repayment of working capital loans for street vendors and collateral-free loans to women self-help groups. (Dr Richa Sharma, 2021) highlights that the Self-help group as a self-reliant entity plays a vital role in the upliftment of the poor. In many nations, cultural and social barrier prevents women from accessing microfinance. Where self-help groups provide loans to women without collateral, MFIs provide large loans to women clients to meet the business needs of the entrepreneurs; as per the (Salla, 2020) during pandemics, many small entrepreneurs are unable to complete projects due to the disruption in the supply chain. This has resulted in the widening of the inequalities among men and women. The inequalities impact the plight and the living standard of the poor (Centre, 2021). Despite all these challenges, the United Nations has identified 992 measures as policy measures to improve the plight of the poor, (UNDP, 2020). The Government of India, during the second wave of COVID 19, introduced a particular subsidy scheme under Pradhan Mantri Jan Dhan Yojana (Ministry of Rural development, 2020). Most of the literature highlights that women entrepreneurs are less likely to start and control a business. As per International Labour Organization, women are both a catalyst and barometer of gender equality. Various literature suggest that the pandemic has adversely impacted the Self-help groups and home-based workers. Due to the pandemic that ended in May 2020, the 6.33 crore Micro, small and medium companies have been adversely impacted due to the Work from Home restrictions. Compared to the urban counterparties, the rural counterparts have exhibited resilience amidst the pandemic (Buteau, S and A Chandrasekhar, 2020). According to the literature, despite a push, the women entrepreneurs face innumerable challenges such as increased household conflicts, increased share of unpaid work, and unlikely to receive relief packages. Overall, the borrowing pattern of the households in the sample reflects the actual borrowing pattern of different entities, and the same has been severely impacted during the COVID 19. This study seeks to measure how the gender characteristic of the household affects the borrowing of the members. From the data analysis, the families dominated by men have more propensity to borrow. This applies to all the sources of finance compared to females during COVID 19. The poverty score, which reflects the asset ownership of the household, is a proxy that has a positive relationship with wealth. Higher the poverty scores more elevated, the asset ownership, and better the household's capability to borrow from the Self-help group, Microfinance institutions, banks, nbfc and other sources such as shops and moneylender. However, for MFI borrowing, lower the asset ownership higher is the probability to get loans or credit. As per the ethos of MFI lending, the poor people generally can borrow from MFIs at lower costs. People in our sample are mainly entrepreneurs and farmers, and they have a higher probability of borrowing. Level of education of householder's impact access to finance from the formal financial institutions does not impact access to finance from informal associations, (Morduch, 1999). This implies that asset ownership and credit offtake are positively related in the case of a loan from the banks, microfinance institutions, and moneylenders. Except for the shops and NBFC, the decline in asset ownership does not lead to a decline in credit creation.

Table 4. Marginal effects of borrowing from different Microfinance sources across income categories during the COVID 19 Months of May-August 2020

	SHG	BANK	MFI	NBFC	Shops	Moneylender
<36000-5,00,000	-0.0145*** (0.002)	0.263*** (0.0431)	0.000074 (0.0008)	0.00559*** (0.0019)	0.0334*** (0.004)	-0.0104*** (0.0019)
5,00,000-10,00,000	-0.0104*** (0.0029)	-0.0182 (0.012)	-0.0021 (0.0018)	-0.0033 (0.0057)	0.0343*** (0.011)	-0.014*** (0.002)
10,00,000-36,00000	0.0026 (0.176)	-0.0084 (0.053)	0.0017 (0.328)	0.0120 (0.027)	0.0009 (0.0003)	0.0164 (0.0119)

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Percentile distribution of income shows that in rural India during COVID 19, in high income group no borrowing took place in the high-income groups. And in low-income group borrowing took place through shops and banks.

Research Problem 2: To estimate the impact of the Self-help group borrowings on the Income of the members of the group during COVID 19

An essential problem in causal inference is ensuring that there is no self-selection bias in selecting the subjects to the treatment and control group. In our study, May April 2021 was the period of a severe second wave of COVID 19. We used the Consumer Pyramid Household Survey to conduct propensity score matching to correct the sample selection bias due to the obvious differences in the treatment and control groups. This study uses the Kernel Matching method to match the Treatment and the control group by utilizing similar items in terms of their observable characteristics. In this study, we intend to test the impact of borrowings from the self-help groups on households and households are selected based on the pre-treatment covariates, and it leads to an unbiased estimate as to the outcome the Average Income of the family is independent of the assignment to Treatment conditional on the covariates that are pre-treatment. Initially, the number of covariates in our study is significant, and Kernel matching allows us to match the households on covariate selected through the natural weighing scheme. The following table will display all the selected control variables for matching.

Table 5. Description of variables used in statistical analysis

Construct	Variable Reason
Gender	It refers to the gender of the household. There are two categories. Female dominated if the home is of the majority of females, Dominated by females, all the females. The male category comprises of all the males, dominated males, and majority males, and a balanced group
Education	This variable refers to whether the members of the households can read and write or not. Household, if illiterate, is considered not able to read and write. Whereas the variable household literate, graduate, matriculate with all levels is deemed literate in the study. This is a binary variable with a value of 1 for literate and 0 for illiterate
Occupation	Occupation comprises of members who are entrepreneurs, and small marginal workers and farmers are considered as self-employed entrepreneurs and given a value of 1. And the white-collar employees who are considered unemployed are given a value of 2
Migration	Migration has a binary value that takes value one if the subject has migrated and 0 if the issue has not migrated
Region	Region refers to the area to which the subjects belong. It takes the value of 1 for the rural part and 0 for the urban region
Score	Score refers to the Poverty score calculated by aggregation of an individual's assets. Higher value lowers the risk of Poverty

The selection of the covariates for matching is adhoc and based on earlier literature.

The summary of the data is given below:

Table 6. Descriptive statistics for the sample

	Mean Average	Standard Deviation	Total units
Gender	36.99% Males		1,41,454
Education	99.6% are educated		1,41,454
Occupation	29.84% are entrepreneurs and self-employed		1,41,454
Migration	0.038% migrated		1,41,454
Regional	35.5% live in the rural region		1,41,454
Score	30.4 is an average score	12.3	1,41,454
Income	Rs 16,619 is the average income	15,747	1,41,454

In this study, we have taken the data for May-August2021, which comprises 1,41,454 responses. This period corresponds to the second wave of COVID 19 illness, during which the COVID 19 wave was extremely severe. There are 36.99% males in the data or 52,323 male observations. In this data set, approximately 1,40,888 are educated, and 54 have shifted or migrated to the other city. Of the entire dataset, about 50,216 are living in rural areas. During this period, the average Poverty score in the data set is 30.4. The average Income in the data areas, the average for the past four months, is approximately Rs.16,619.

Graphical summary of data

A summary of the dataset is given below in the dataset. Data distribution for the Average Income of the respondents in the control group with 0 SHG (Self-help borrowings) and the treatment group with SHG (Self-help group) borrowing is given in the graph below.

The distribution is also represented with the Box diagram. The box diagram shows that the Median for the two groups is different. Those respondents who have acquired Self-help group borrowing have a higher median. The distribution for the two groups is depicted with the Box diagrams.

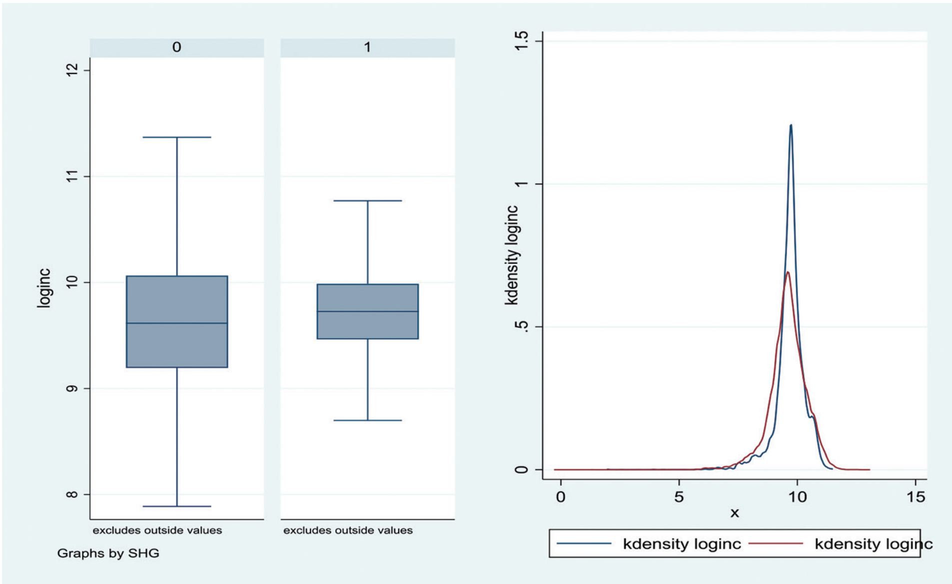

Figure 1. Combined graph for the Box Plot and the Kernel Density graph

This gives us an idea that during May-August 2021, the households with SHG (Self-help group) have a lower average income despite a lower median. This is also depicted in the distribution that is shifted to the left (Curve in red)

Hypothesis testing

H0: Group means for members without SHG Loans and with SHG Loans are not different from each other

Results of t-test

Table 7. Results of the t-test

Group	Observation	Mean	Std Error	Std Deviation	LCL	UCL
Non-SHG	1,37,451	16,568.26	42.78	15863.66	16,484.39	16,652.12
SHG	4,003	18,382.14	171.96	10,880.05	18,044.99	18,719.28
Combined	1,41,454	16,619.59	41.86	15,747.18	16,537.53	16,701.65
Difference		-1,813.879	252.444		-2,308.66	-1,319.093

Difference (No SHG) – Difference (SHG)

Hypothesis: The difference between the mean of no SHG and SHG is 0

Results populated a t value of -7.185 and degrees of freedom 1,41, 452

Hypothesis: The difference between the means of 2 groups is less than 0

Probability = 0.000

Hypothesis: The difference between the means of 2 groups is equal to 0
Probability = 0.000
Hypothesis: The difference between the means of 2 groups is greater than 0
Probability = 1.000

Using a two-sample t-test in a bidirectional hypothesis, we reject the hypothesis that the means between the two groups are equal. We accept the hypothesis that the difference between the non-SHG borrowers and borrowers is more significant than zero. However, this does not establish that the Non-SHG Borrowers have a higher income than SHG Borrowers. From the data analysis, between the respondents not having the borrowings from the Self-help group and those having loans from the Self-help group, there is a difference of Rs. 1,813.87, and this difference is statistically significant as tested and verified through the t-test.

Propensity Score Matching using Kernel Matching

After discussing the descriptive, we can start Kernel matching. Initially, the data aims to estimate the impact of Self-help groups on the average Income of the borrowers, controlling for some covariates variables such as age, education, Occupation, gender. Using the Mahalanobis distance, the Kernel Matching is achieved.

Using Mahalanobis distance kernel matching the Average treatment effect of SHG Borrowing is calculated Average Income is calculated using the covariates such as age, education, Occupation, gender.

There are several reasons for not using the traditional Parametric regression for analyzing the impact of endogenous (non–random) policies, such as allocation to the Self-help groups based on characteristics such as the preliminary information about the other members in the group. The parametric regression analysis suffers from various shortcomings. One could be that the members participating in the self-help group program might be significantly different from those not participating in the self-help groups. These differences might be significant in affecting the desired outcomes. Generally, members who borrow from the Self-help group do not have any collateral, and the other members do not have any information about the creditworthiness of the other members in the group. Berhman, Cheng, and Todd (2004) discuss the shortcomings of the Parametric regression. Thus, the respondents in the participating group may be incredibly different from the non-participant group. With the use of the Matching methods, the differences between the groups. In this study, we have used the Kernel Matching method to match the respondents into the Control and Treatment group. Using the Kernel Matching method, we have calculated the ATT (Average Treatment effect on Treated and Naïve Average Treatment Effect). Both these statistics show a high level of significance on a 5% confidence interval from the statistics calculation. There are many different methods to match the Treatment and the Control group based on various algorithms, and one such method is the Multivariate Distance Matching (MDM) method. This metric is based on matching the Treatment and the control group based on the distance metric that measures the proximity between the observations in the Multivariate space of X. This method makes use of the observations that are "close "and are not "necessarily equal" as the matching happens. The standard approach to the matching used in this study is given below

$$D_M(\vec{x}) = \sqrt{(\vec{x}-\vec{\mu})^T S^{-1}(\vec{x}-\vec{\mu})}$$

The formula above is a distance metric where an appropriate scaling matrix is used. The Mahalanobis matching in the given method is equivalent to the Euclidean matching based on standardized and orthogonalized X. There are various different matching algorithms that are used to find the matches that are based on the MD (Mahalanobis distance) and determine the matching weights. This matching could be on the basis of Pair matching, Nearest neighbour matching, Caliper matching, Radius matching, and Kernel Matching. In the Pair matching (One to one matching without replacement), for each observation, i in the treatment group, the observation j in the group is located in the control group on the basis of the smallest Mahalanobis distance. In the nearest neighborhood, for each observation I in the treatment group, the matching method finds the k closest observations in the control group. In this method, the single Control can be used multiple times. In the case of the Caliper matching method, like nearest neighbour matching, only use controls for which the Mahalanobis distance is smaller than the threshold. In the case of the Radius matching, we use all the controls as matches for which the Mahalanobis distance is smallest than some threshold c. The method that we have used in the study is Kernel matching which, like radius matching, makes use of all the controls as matches for which MD is smaller than some threshold c. But in the case of Kernel Matching, more considerable weight is given to the controls for which MD is small. The results for matching based on the Mahalanobis distance is shown below:

Matching Statistics

Table 8. Matching through Kernel Matching using Mahalanobis distance

	Matched			**Controls**			
	Yes	**No**	**Total**	**Used**	**Unused**	**Total**	**Bandwidth**
Treated	3,899	0	3,899	1,18,442	147	1,18,589	0.606

Treatment Effect

Table 9. Calculation of the Average Treatment Effect and Naïve Average Treatment Effect

	Coefficient	**Std Error**	**T**	**P> |T|**	**LCL**	**UCL**
ATT	0.0819	0.0101	8.08	0.000	0.062	0.101
NATE	0.0982	0.0100	9.75	0.000	0.078	0.118

Through Kernel Matching using Mahalanobis distance, we generated 3,899 households that were treated and received the SHG Borrowing and were matched against the 1,18,442 control households. The treatment effect showed the SHG Borrowings had a relevant impact on the average Income of the household.

Table 10. Matching variances on the basis of Covariates

	Raw Score			Treated Matched (ATT)		
Variances	**Treated**	**Untreated**	**Ratio**	**Treated**	**Untreated**	**Ratio**
Score	0.221	0.181	0.099	0.221	0.221	-0.000
Education	0.987	0.995	-0.093	0.987	0.987	-0.000
Occupation	0.509	0.327	0.374	0.509	0.509	0
Region	0.276	0.323	-0.140	0.276	0.276	0
Score	30.48	30.44	0.003	30.48	30.44	0.003

The data from Kernel Matching across the dimensions such as Score, Education, Occupation, Region show that in the matched sample the variances have been reduced drastically.

Table 11. Matching means on the basis of Covariates

Means	**Treated**	**Raw Untreated**	**Ratio**	**Matched (ATT) Treated**	**Untreated**	**Ratio**
Score	149.133	152.98	1.160	0.172	0.172	1.000
Education	0.0124	0.004	3.047	0.0124	0.0124	1.000
Occupation	0.249	0.220	1.134	0.249	0.249	1.000
Gender	0.172	0.148	0.913	0.200	0.200	1.000
Region	0.200	0.219	0.974	149.133	145.055	1.028

From the analysis of the results given above, we find that the mean between the Treated and the Untreated groups has been reduced drastically. Also, the results in the matching of the treated and the untreated groups are plotted using the graph.

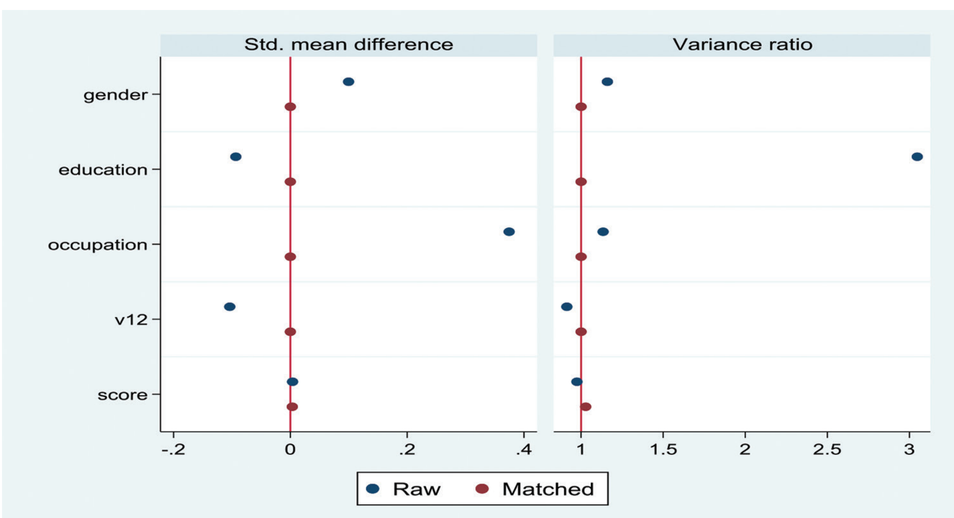

Figure 2. Standard matching graph between the Treated and Untreated group

The analysis of the data reveals that there is sufficient matching between the Treatment and the control group. The box plot for the data is given here. The data reveals a drastic improvement in the matched group in terms of the Average Treatment effect on treated.

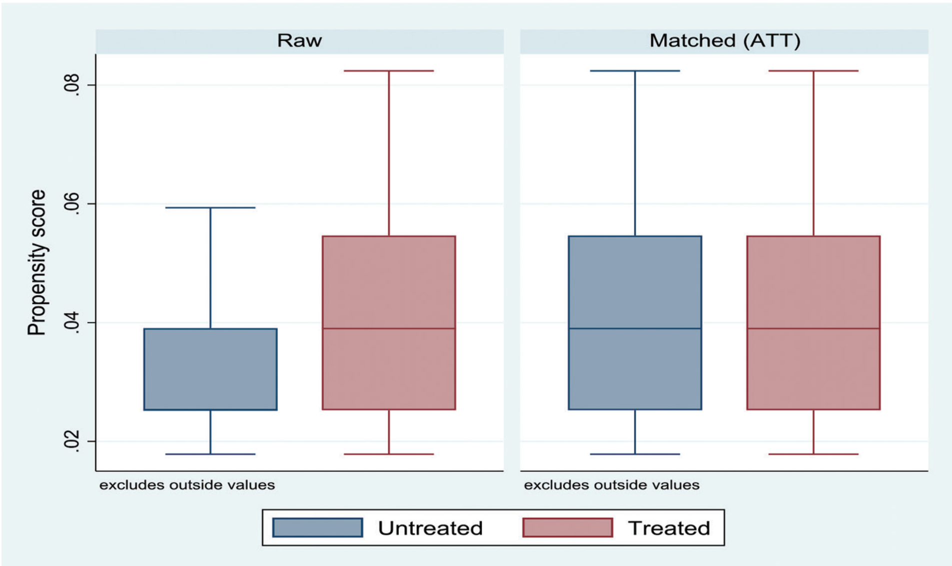

Figure 3. Box plot for the treated and untreated group

Kernel Propensity Score Matching for evaluating the impact of SHG Borrowing in the Second wave of pandemic under particular collateral loan free program (Average Treatment Effect of Treatment on Treated, Average Treatment Effect for Controls) on Income.

Table 12. Average treatment effect, Average treatment Effect on treated and Average treatment effect on Control

Log Income	Coefficient	S.E.	T	P>t	95% conf.	interval
ATE	0.102	0.011	9.080	0.000	0.080	0.124
ATT	0.110	0.010	10.870	0.000	0.091	0.130
ATC	0.102	0.011	9.010	0.000	0.080	0.124

Table 13. Multivariate distance kernel matching (Using the Bootstrap replications)

	Observed	Bootstrap			Normal	Based (95% CI)
Log Income	**Coefficient**	**Std Error**	**Z**	**P>z**	**LCL**	**UCL**
ATT	0.1104759	0.0102	10.85	0	0.0905	0.13044

From the analysis of the results of the Propensity Score matching, we find that the average treatment effect, Average treatment effect of treated, and Average treatment effect of Control are all significant. This denotes that there is a substantial difference between the Control and the Treatment groups. In the study, the average treatment effect of Treatment is 0.1104, which implies that the treated group or the members who take the loan from the Self-help groups have 11.04% higher Income than the control group. This means that self-help group borrowing has a relevant and significant impact on the average Income.

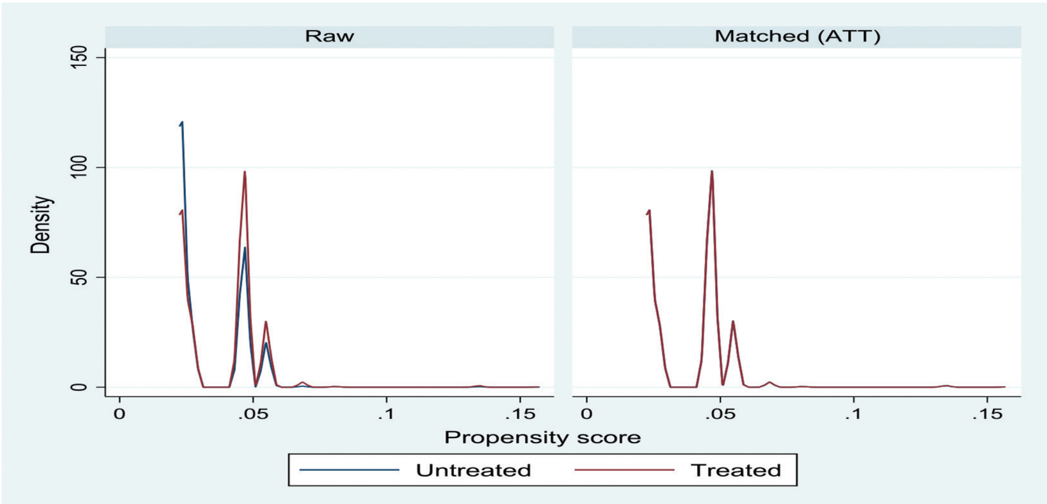

Figure 4. Kernel Matching between treated and the matched group

The two study groups (SHG Borrowing Vs. Non-SHG Borrowing) differed on several significant characteristics such as the Poverty score, gender of the household, education of the household, Occupation of the household, and the region of the household. Further, to adjust for the standard errors, bootstrapping was performed. From the data analysis, Average treatment effect, Average Treatment of the control group, Average treatment effect, and Naïve average treatment effect are all significant as the Z statistics for the analysis are highly significant.

Table 14. Standard Errors – Bootstrapping to calculate NATE, ATE, ATT, ATC, VCE (Bootstrap)

	Observed	Bootstrap			Normal	Based
Log Income	**Coefficient**	**S.E.**	**Z**	**P>Z**	**[95% conf.**	**interval]**
ATE	0.1021	0.0118	8.65	0	0.079	0.1252
ATT	0.1105	0.0107	10.32	0	0.0895	0.1315
ATC	0.1018	0.0119	8.58	0	0.0786	0.1251
NATE	0.0983	0.0107	9.19	0	0.0773	0.1192

In this study, the Lincom test computes the point estimates, standard errors, t or z statistics, p values, and confidence intervals for the linear combinations of coefficients after the estimation. After performing the Lincom tests, we find a significant difference between the Average Treatment of Control and the Average Treatment of treated. This establishes a substantial difference between the Control group and the Treated group. Also, the average treatment effect, average treatment effect on treated, average treatment effect on Control, and naïve average treatment effect have a value of 10.21%, 11.05%, 10.18%, and 9.83%. This implies that the Self-help group borrowing impacts the Income of the group.

Diagnostic tests

After estimating the model, it is essential to ensure that the assumptions hold for the model. The first assumption in the model is that the Average Treatment effect of Control is different from the average treatment effect of Treatment. Based on the diagnostics, the Average treatment effect of Control is different from the average effect of Treatment on treatment. This is significant with highly relevant Z statistics.

Lincom test (ATC = ATT)

Table 15. Diagnostic test or Lincom test

Log Income	Coefficient	Std. Error	Z	P>z	[95% conf.	interval]
-1	0.0121982	0.0018383	6.64	0	0.0085953	0.0158

Chi-Square Test

Hypothesis ATT= ATC
Results: chi2(1) = 3.04
Prob > chi2 = 0.0811

Linear Propensity Scoring

(Rosenbaum, P.R. and Rubin, D, 1985) Their research study has highlighted that matching linear propensity scores can be highly effective in reducing bias. The literature argues that the exact matching in many of the ways is not an ideal method, (Imai K, King G, Stuart EA. , 2008) highlights that the exact matching is not in many ways excellent. The primary difficulty is that the same Mahalanobis distance measure does not work very well when X is high dimensional. Exact matching often leads to many individuals not being matched, resulting in more considerable bias than if matches are inexact but more individuals remain in the analysis. Further, the author argued that matching balancing scores and the propensity score is sufficient. The propensity score is the conditional probability of being assigned to the treatment group given the individual's covariates. This method, unlike the Mahalobinas, uses vector observation uses the propensity score, which is a univariate score. The average treatment effect is the intermediate outcome level for those in the treatment group minus the average outcome level of those in the control group after conditioning on the Propensity score. The results for this is valid only for the common support or the observations within the common support, which is a range of propensity score for which these are both the control and treatment observations. We conduct a Propensity score matching with Occupation as the basis of exact matching. Propensity score matching with Occupation provides a statistically relevant result.

Exact matching with Occupation as a criterion

Propensity score matching with matching on basis of Occupation

Table 16. A propensity score matching based on Occupation

	Yes	No	Total	Used	Unused	Total	
Treated	3899	0	3899	117866	723	118589	0.00E+00

Based on the Propensity Score Matching on the basis of exact match, we find 3,899 exact households. Common support is the range of propensity scores for which the positive probability of both observing the Control and the Treatment group is 1.

Average Treatment Effect on Treated

Table 17. Average Treatment Effect on Treated based on Propensity Score Matching

Log Income	Coefficient	Std. Error	T	P>t	[95% conf.	interval]
ATT	0.10648	0.01016	10.48	0	0.08656	0.1264

The analysis of the results and the statistics generated (Average Treatment Effect on treated) signify that the Average Treatment effect of treated is 0.106, which implies that the treated group had an average income of 10.6% higher than the control group. This difference is also statistically significant.

Rosenbaum Bounds

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.141	0.141	0.12683	0.15508
1.25	0	0	0.09719	0.18443	0.08261	0.19886
1.5	3.40E-14	0	0.06062	0.22057	0.04538	0.2356
1.75	0.0002	0	0.02901	0.2519	0.01319	0.26771
2	0.445	0	0.00114	0.27969	-0.0154	0.29613
2.25	0.9979	0	-0.024	0.30463	-0.0415	0.32176
2.5	1	0	-0.0472	0.32731	-0.0655	0.34506
2.75	1	0	-0.0686	0.34803	-0.0879	0.36634
3	1	0	-0.0887	0.36709	-0.1091	0.38593

(Rosenbaum, P.R. and Rubin, D, 1985). Argues that the matching relies on the observational data, which does not allow us to measure the causal effects of findings. However, matching allows for testing how robust our results are with respect to the omitted variable. Omitted variables are not included in the data and are not measurable, and these variables might introduce spurious correlations, which can undermine our findings. Rosenbaum bounds aim to simulate how strong the unobserved factors must be to undermine the effects in matching. It is aimed to calculate gamma values in steps 1 to 3 in steps of 0.25. Gamma is an unobservable value that increases the chance of being included in the treatment group. All critical values are around 1.75, as above the values cross the threshold. Suppose there is an unobserved factor that influences the chance to be a significant result. Results are robust as the unobserved factor would need to affect or influence our treatment strongly.

Conclusion

The study concludes that rural regions witnessed a decline in borrowing from Microfinance institutions, Moneylender, banks, NBFCs, and Shops. COVID 19 led to a reduction in the borrowing from the SHGs, Bank, Microfinance institutions, Shops, and Moneylender. Males saw an increase in borrowing from Self-help groups, Banks, Microfinance institutions, Nonbanking finance companies, and the Moneylender. Literate members witnessed a decline in the borrowings from different sources including Self-help groups, non-bank finance companies, and shops. From the t-test, there is a significant difference in the average income of the borrowers who have taken the loan from the SHGs and those who have not taken the loans from the Self-help groups. The box plot exhibits that the borrowers who have taken the loan from the Self-help groups have higher median income than the other income sources. The distribution for borrowers who have SHG loans is a better fit than Non-SHG loans. The borrowers who have taken loans from the Self-help groups have a higher median income than those who have not taken the loans. Since there is always the chance of endogeneity and self-selection in a random allocation. We achieve the matching using Kernel matching with Propensity Matching in the given sample. The results show that the difference between the members who have taken loans from the SHGs (Self-help groups) and the non group is significant.

References

Deshpande. (2020). The covid-19 pandemic and lockdown: First effects on gender gaps.

Albouy, D. (2004). Program Evaluation and the Difference in Difference Estimator . *University of Berkeley* . University of Berkeley .

Arunachalam & Crentsil . (2021). Financial inclusion in the era of COVID 19 . *Financial Inclusion Advocacy Centre* .

Buteau, S and A Chandrasekhar. (2020). *Economics Political Weekly* . Retrieved from https://www.epw.in/node/158375/pdf: https://www.epw.in/node/158375/pdf

Centre, U. I. (2021). *https://www.dfc.gov/our-work/financing-for-small-businesses-and-women-entrepreneurs*. Retrieved from US Development Finance Corporation: https://www.dfc.gov/our-work/financing-for-small-businesses-and-women-entrepreneurshttps://www.dfc.gov/our- work/financing-for-small-businesses-and-women-entrepreneurs

Chakma, H. C. (2020, July 2). *Financial Inclusion and Resilience: How BRAC's Microfinance Program Recovered from the West Africa*. Retrieved from Global delivery initiative: https://www.globaldeliveryinitiative. org/sites/default/files/

Coate, B. &. (2013). On the viability of group lending when the Microfinance meets the market : A consideration of Beasley & Coate Model . *Journal of Emerging Markets* .

Consumer Pyramids Household Survey. (2020). *Houshold Groups.* Centre for Monitoring Indian Economy Pvt Ltd.

Counts, A. (2008). Small loans, big dreams: How nobel prize winner muhammad yunus and microfinance are changing the world. *John WIley & Son*.

Desai & Joshi. (2013). Collective Action and Community Development: Evidence from Self-Help Groups in Rural India. The World Bank Economic Review. Advance Access. *World Bank Economic Review. Advance Access.*

Dr Richa Sharma. (2021). EMPOWERING WOMEN SELF HELP GROUPS THROUGH microfinance during the COVID 19. *Indian Journal of Finance and Banking*.

Duflo, E. (2012). Women Empowerment and Economic Development . *Journal of Economic Literature* , 1051-1079.

Green, B. T. (1960). Complex analyses of variance: General problems. Psychometrika . *Psychometrika*, 25, 127–152 (1960).

Imai K, King G, Stuart EA. (2008). Misunderstandings among experimentalists and observationalists in causal inference. *Journal of the Royal Statistical Society Series A*, 171(2):481–502.

Joshi, G. (2019). An analysis of women's self help group involvement in microfinance program in India. *Rajagiri Management Journal* .

Kumar, T. A. (2005). Role of microfinance in disaster mitigation. Disaster Prevention and Management:. *An International Journal*, 14(2), 176–182.

Liegey, V. N. (2020). Exploring Degrowth: A CriticalGuide. *London: Pluto Press.*

Long, J. D. (2012). *Longitudinal data analysis for the behavioral sciences using R. Sage.*

M Yunus. (2003). Banker to the Poor: MicroLending and the Battle against the World Poverty. *New York Public Affairs*.

Maclean, K. (2010). Capitalizing on women's social capital? Women-targeted microfinance in Bolivia. Development and Change,. *Development and Change*, 41(3), 495–515.

Malik, K. M. (2020). COVID-19 and the future of microfinance: Evidence and insights from Pakistan. . *Oxford Review of Economic Policy,* , 36(1), S138–S168.

Mayoux, L. (1999). Questioning virtuous spirals: micro-finance and women's empowerment in Africa. *Journal of International Development* , 957-984.

Ministry of Rural development. (2020). *Press Information Bureau of India*. Retrieved from https://pib.gov.in/newsite/PrintRelease.aspx?relid=200951.

Mirman, D. (2014). *Growth curve analysis and visualization using R.* Boca Raton, FL: CRC Press.

Muravyev, A., Talavera, O., & Schäfer, D. (2009). Entrepreneurs' Gender and Financial Constraints : Evidence from International Dias . *Journal of Comparative Economics,*, 270-286.

Murshid N. (2021). "Innovations" During COVID-19: Microfinance in Bangladesh. *Microfinance in Bangladesh. Affilia. November 2021*.

Murshid, N. S. (2020). Examining microfinance participants' use of neoliberal language in Bangladesh. . *Journal of the Society for Social Work and Research,* , 11(2), 285–312.

NABARD Department of Economic Analysis. (2020). *Impact Assessment of COVID 19 on India Agriculture and Rural Economy.* New Delhi: NABARD.

Nelson, A. (2016). Your money or your life": Money and socialist transformation. Capitalism Nature Socialism. *Capitalism Nature Socialism*, 27(4): 40–60.

Niels Hermes, R. L. (2005). Peer Monitoring, Social Ties amd Moral Hazard in Group lending programmes evidence from eritet. *World Development* , 149-169.

Observatory, E. (2020, September 6). *Aid & International Development*. Retrieved from https://www.economicsobservatory.com/: https://www.economicsobservatory.com/

P. Christian, E. K. (2019). Safety nets and natural disaster mitigation: evidence from cyclone Phailin in Odisha. *Climatic Change, 153 (1–2) (2019)*, 141-164.

Roodman, D. M. (2014). The impact of microcredit on the poor in Bangladesh: Revisiting the evidence. The Journal of Development Studies. *The Journal of Development Studies*, 50(4), 583–604.

Rosenbaum, P.R. and Rubin, D. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. The American Statistician. *The American Statistician*, 39, 33-38.

S. Marlow, D. P. (2005). All credit to men? Entrepreneurship, finance, and gender. *Entrep. Theory Pract*, 717-735.

Salla, S. (2020). How ill the COVID 19 AFFECT WOMEN WNTREPRENEURS.

Sangwan et. al. (2021). Covid-19 pandemic: Challenges and ways forward for the Indian microfinance institutions. *The Journal of Public Affairs*.

Sudip Bandyopadhyay. (2021, March 9). *MFIs Champion An Ecosystem Of Grassroot Women Entrepreneurs For Sustainable Progress*. Retrieved from The businessworld : https://www.businessworld.in/article/MFIs-Champion-An-Ecosystem-Of-Grassroot-Women- Entrepreneurs-For-Sustainable-Progress/09-03-2021-383355/

Susilawati & et.al. (2020). Impact of COVID 19 Pandemic on economy of Indonesia . *Budapest International Research and Critics Institute (BIRCI-Journal) : Humanities and Social Sciences*.

The Government of India. (2020, August 14). *Atmanirbhar Bharat*. Retrieved from Atmanirbhar Bharat: https://aatmanirbharbharat.mygov.in/

The Government of India. (2020). *Pradhan Mantri Jan Dhan Yojana*. Retrieved from Pradhan Mantri Jan Dhan Yojana: https://pmjdy.gov.in/

Townsend et.al . (2003). Microcredit and Mechanism Design. *Journal of the European Economic Association*, 468-477.

Treichel, M. A. (2006). Women-owned businesses and access to bank credit: evidence from three surveys since 1987. *Ventur. Cap.*, 51-67.

UNDP, U. W. (2020). Retrieved from Gender Response Tracker. Global Fact Sheet, Version 1.