

# Coping through Credit: Effect of Microfinance on Informal Lending after Disasters

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# Disasters and Coping

- 90% of disasters have been caused by weather-related events - 6,457 weather-related disasters were recorded worldwide over the last 20 years
- These have claimed 606,000 lives - average of 30,000 per annum
- An additional 4.1 billion people injured, left homeless or in need of emergency assistance.
- Flooding alone accounted for 47% of all weather related disasters (1995-2015)
- Floods also affected 2.3 billion people, 95% of whom live in Asia

# Disasters and Coping

- EM-DAT reported a total of US\$ 1,891 billion due to weather related disasters between 1995 to 2015
- UNISDR's 2015 GAR estimates economic losses from disasters at an average of US\$ 250 billion to US\$ 300 billion each year
- About US\$ 709 billion losses suffered by Asia alone
- The economic losses account for about 5 percent of the GDP of low income countries as against 0.2 percent for high income countries

# Consumption Shortfalls Post Disasters

- Several studies have highlighted the severe shortfalls in consumption post disasters
- Typically, households face a shortage of food, fodder due to loss of income post disaster. This can be precipitated through loss of agricultural produce, unavailability of work, destruction of assets
- Studies have also documented a rise in prices of essential commodities which in effect push items outside the consumption basket of households

# Consumption Smoothing Post Disasters

- Consumption smoothing essentially involves risk-averse agents who in the inter-temporal context prefer a smooth consumption profile over an uneven one
- Therefore to address aggregate shocks caused by disasters these households would tide over consumption shortfall in period  $t_0$  by borrowing in the current period from period  $t_1$  in the future
- In the context of our study, this prepares the intuitive ground for expecting people to 'borrow' for consumption after disasters

# Credit and Consumption Smoothing

- Borrowing is one of the common ways of consumption smoothing post disasters wherein households take small consumption loans from formal or informal sources
- Other ways could include stress migration, selling household assets, changing consumption or spending portfolio
- Access to credit however can act as a stop gap 'informal insurance' mechanism which is commonly leveraged by low income rural households in the absence of an insurance market

# Credit Market Imperfections

- The rural credit market however is ridden with the challenges of large-scale credit constraints and credit rationing
- Due to the inherent information asymmetries in these markets, households face:
  - **Credit Constraints** : The lenders are not willing to give credit beyond a limit to prevent defaults
  - **Credit Rationing** : As there is limited credit available and the returns to getting funds are high, there is greater demand than supply of credit and only a limited number of households get the loans
- Therefore often we find households who are most in need of credit, being left out

# Additional Liquidity through Microfinance

- Microfinance is a tool which tries to address these credit market imperfections by using the means of 'social capital'
- Typically, in the microfinance setup there are small groups formed within villages which collectively engage in saving and borrowing from microfinance institutes
- Information asymmetries are thus addressed through the non-market route of social interactions which in-turn improves credit access for households



# Additional Liquidity through Microfinance

- However, the disbursement of loans through microfinance is restricted only to the purpose of running or setting up business or agriculture, and its use for consumption purposes is not encouraged
- There are limited number of MFI loans given out for consumption, thus possibly limiting its relevance in a post disaster setup.
- However, the usage of loans is not very strictly monitored, and borrowers can in effect use the loans for consumption purposes
- We postulate that microfinance by injecting into the post disaster setting, additional liquidity and a good dose of social capital, enables higher informal lending across households after disasters

# Research Question

Does microfinance help in increasing liquidity for consumption smoothing in households post disasters?

# Literature

- This paper takes off from the work of Eswaran and Kotwal (1990) where they build a formal model to show that access to credit is a major determinant of consumption smoothing
- They also showed that risk pooling is can prove to be advantageous for households when credit flows from households who are not affected by floods to those who are
- A further addition to this comes from work by Udry (1990) where he studies drought affected agricultural households in Northern Nigeria engaging in informal insurance mechanism through small informal loans

# Literature

- For the current data set as well, del Ninno et al (2000) show that borrowing is the main coping strategy of flood affected households. 60% of the sampled households were in debt in the months following the floods
- We now bring in focus the presence of microfinance post disasters. Several studies (Khandker,2007; Bechetti and Castriota, 2011) show that the presence of microfinance is helpful in bringing affected populations back to their pre-disaster level of welfare

# Literature

- These studies however do not highlight how does the effect play out. Work has been done to show how microfinance acts as a recapitalization agent for businesses post disasters and the study was able to establish the benefits to MFI borrowers (Berg and Schrader, 2012)
- We take off into considering the use of microfinance, where studies look into the use of MFI loans as 'a set of money-management services' (Morduch, 2013) which essentially says that once the household has access to MFI loans the fungible nature of funds ensures that households use it as they wish, while ensuring servicing of the loan

# Unique Placement of the Question

- Prior studies have highlighted the importance of access to credit for smoothing consumption after disasters, but they have not looked at the means of the same from the lens of microfinance
- Studies done on how microfinance helps after disasters are limited to looking at loans to firms for recapitalisation. They do not focus on household lending behaviour as such
- This study tries to address this lacunae and comes up with a comprehensive understanding of how Microfinance can be useful for households facing severe consumption shortfalls

# Data Set

- We select the FMRSP-IFPRI Dataset on Coping Mechanisms after the Bangladesh Floods 1998 for our study
- This is a panel dataset which tracks 757 rural households across 7 geographical areas affected by the floods at three different points in time. It starts right after the disaster struck, up to a year after the tragedy to see which coping strategies were employed by households and the long term effects of the same
- We focus only on the point of time immediately after the disaster where we observe the coping strategies which were taken course to

# Data Set

- The data set measures important aspects of credit transactions within the sample households by looking at sources of loan, reason for loan, loan given out in cash, interest rate charged, repayment status. We make use of this information extensively to come to our results
- Further the data is also categorized into flood exposure levels using the following index which is constructed based on the damages faced. We make extensive use of these categories as well:

<b>Flood Exposure</b>	<b>Flood Index</b>
Not Exposed	0
Moderately Exposed	1-6
Severely Exposed	7-9
Very Severely Exposed	10



# Analysis

- The analysis is structured into 3 components:
  - General Aggregates and Results
  - Regression Analysis with *thana* level MFI index
  - Regression Analysis with village level MFI index
- At the general aggregate level we try to understand the current loans being given out overall in the data. We also study some disaggregated results across geographical units
- On moving to the regression analysis we construct MFI indices for different levels of geographical units, and then test if they are indeed a factor for higher liquidity post disaster

# Construction of Indices

- We construct an MFI loan index which measures the presence of MFI loans in the particular geographical area by share of loans given out
- These indices are first constructed for the *thana* level, and then at the village level within each *thana*
- By nature of their construct these indices do not show a high level of variance, and thus we try to induce some variance within the data by disaggregating at the village level
- An ideal scenario would have been if we could construct *samiti* or saving group based MFI indices, yet the village level MFI index stands as a good proxy

# Aggregated Results

- We now would look at the lending pattern across households in our dataset, studying the reason for taking loans, followed by looking at the main sources of loans.
- Then we study the pattern of lending across for exposure to see if credit is flowing to high exposure households
- Next we move to disaggregated results across geographical units to understand what are the main sources of loans across these areas

# Reason for Taking Loans

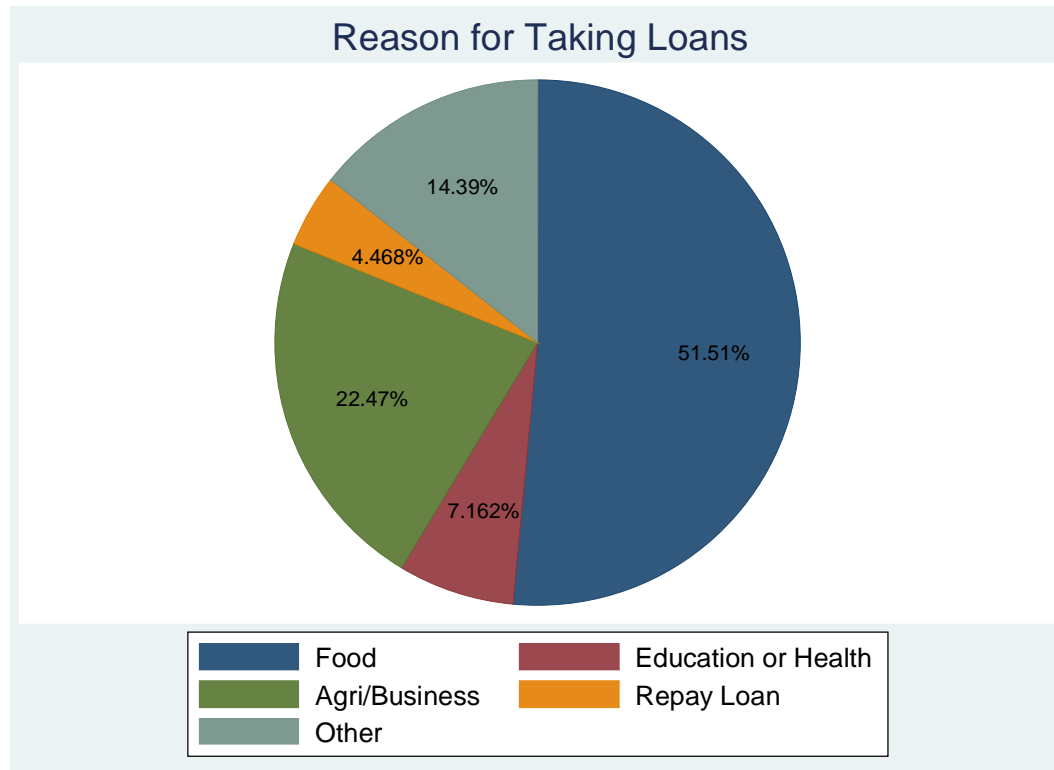


Fig. 1.1

- Primary reason for taking loan is food or consumption
- This is followed by loans for business or agriculture purpose
- We now will see which were the main sources of loans

Source of Loan	Percentage (of total loans given out)	Average amount of loan (in taka)	Average value of loans based on weight in credit market (in taka)
Neighbour	41.48	2482.30	6615.86
Relative	26.38	3041.19	4207.48
Mahajan	12.57	3793.60	2004.85
Krishi Bank	2.98	10278.26	475.30
Grameen Bank	2.72	6630.95	433.83
BRAC	2.59	5537.50	413.09
Other	2.20	2104.00	350.89
Other Cooperative	1.75	3872.22	279.12
Proshika	1.17	6722.22	186.61
Other NGO	1.17	6388.89	186.61
ASA	1.04	4156.25	165.88
Sonali Bank	0.97	6813.33	154.71
BRDB	0.71	4454.55	113.24
GKT	0.71	4818.18	113.24
Government Banks	0.58	11000.00	92.51
GOBL Cooperative	0.32	4700.00	51.04
Jagoroni Chakra	0.19	5666.67	30.30
Employer	0.13	13500.00	20.73
Save the Children	0.06	6000.00	9.57
CARE	0.06	25000.00	9.57
Commercial Bank	0.06	2000.00	9.57
Landowner	0.06	800.00	9.57

Table. 1.1

# Size of Loans and Interest Charged across Exposure

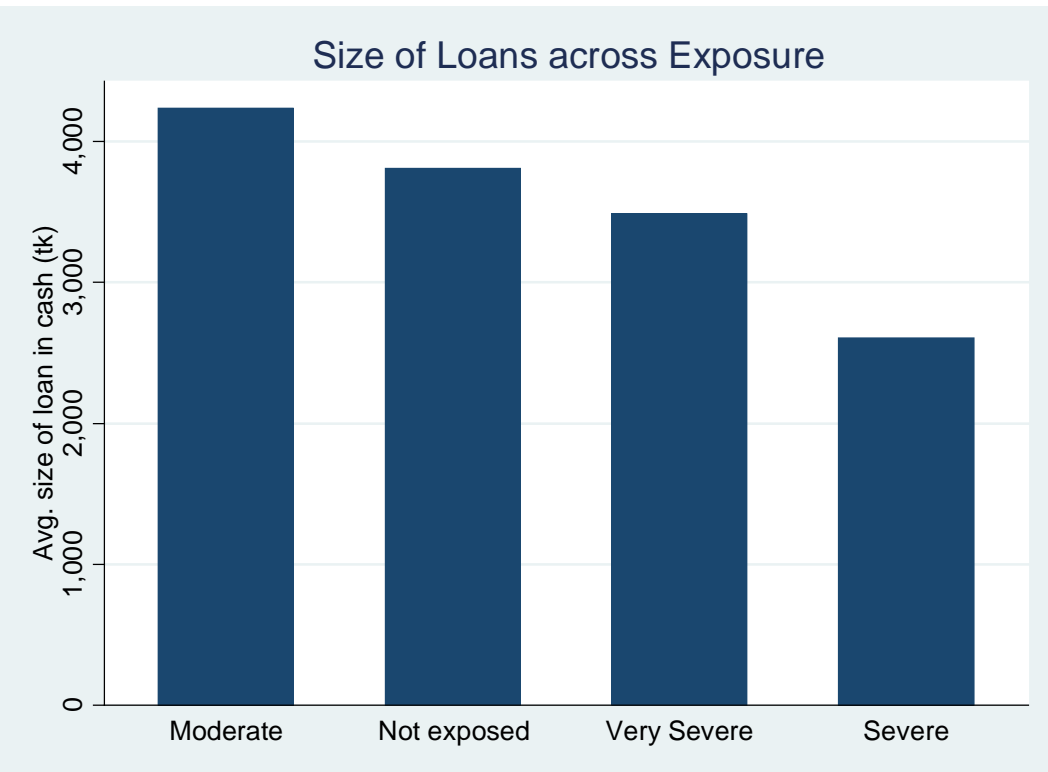


Fig. 1.2

Flood Exposure	Rate of Interest charged (per cent per annum)	Amount of Loan (in taka)
Not Exposed	51.16	3102.64
Moderately Exposed	57.26	3637.16
Severely Exposed	51.22	2097.49
Very Severely Exposed	56.23	2804.98
Average	53.85	2880.49

# Flood exposure of Households across *thana*

Thana	Not Exposed	Moderately Exposed	Severely Exposed	Very Severely Exposed
Derai	32.53	37.37	15.92	14.19
Madaripur	0.0	6.35	31.75	61.90
Mohamedpur	56.17	23.46	17.28	3.09
Muladi	2.24	35.46	51.12	11.18
Saturia	48.13	33.16	8.56	10.16
Shibpur	47.74	10.05	23.12	19.10
Sharasti	6.02	19.91	35.19	38.89

Table 1.2

# Type of Loan across *thana*

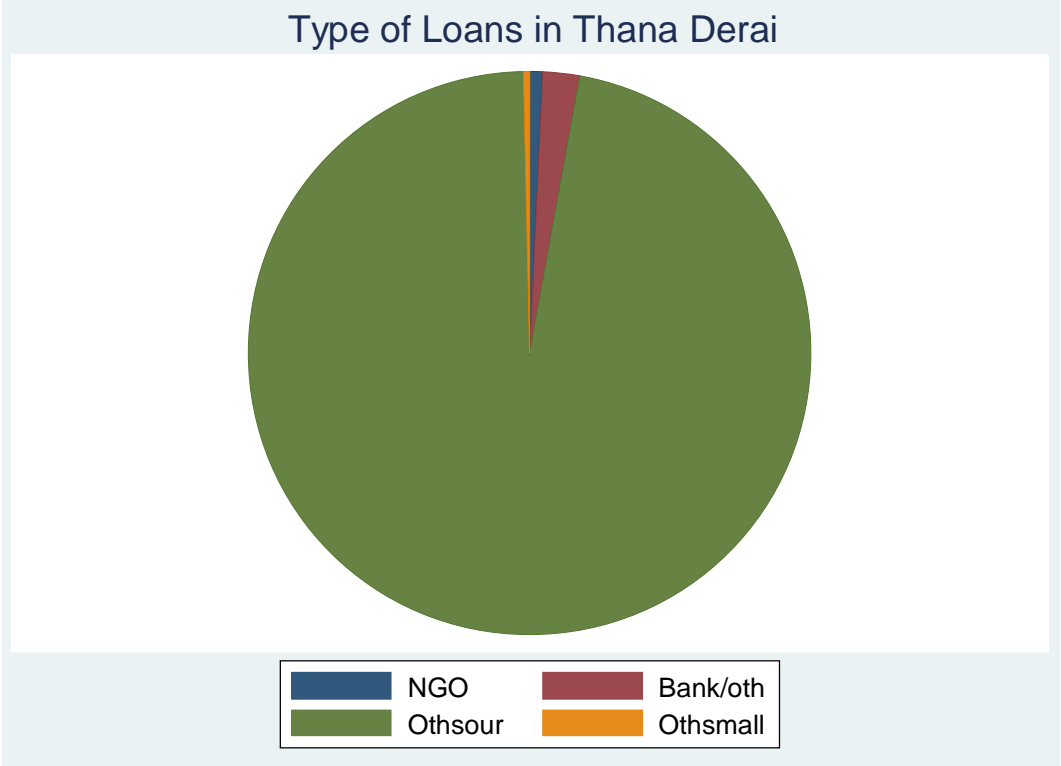


Fig. 1.3

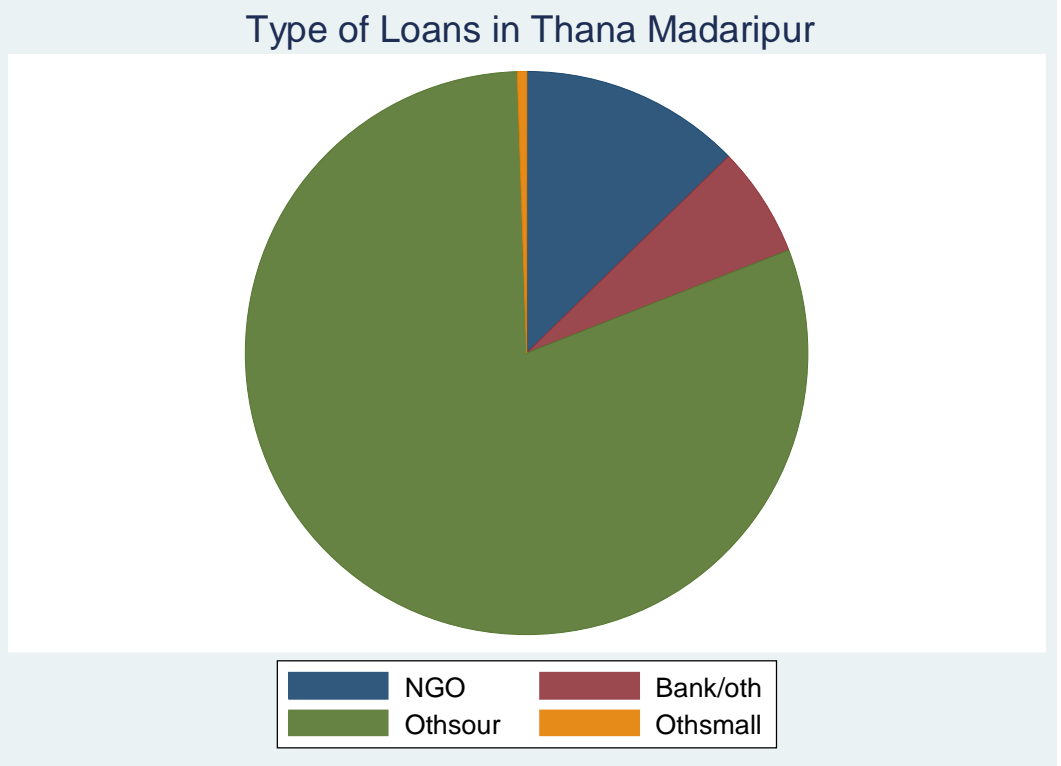


Fig. 1.4



# Type of Loan across *thana*

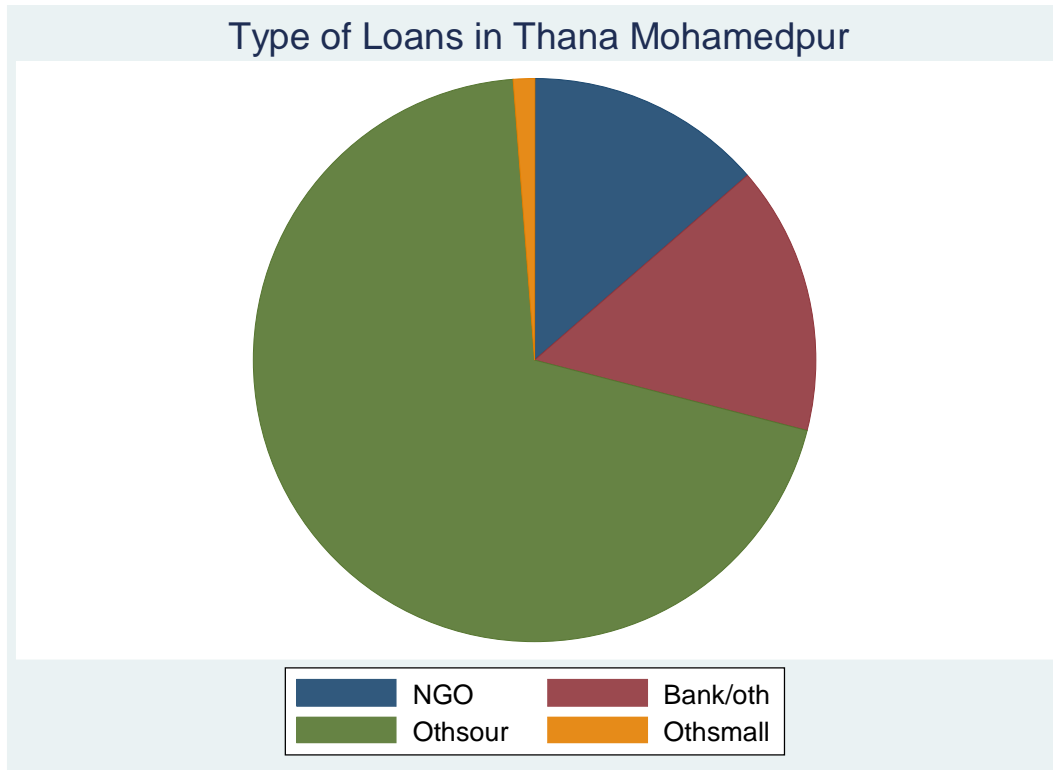


Fig. 1.5

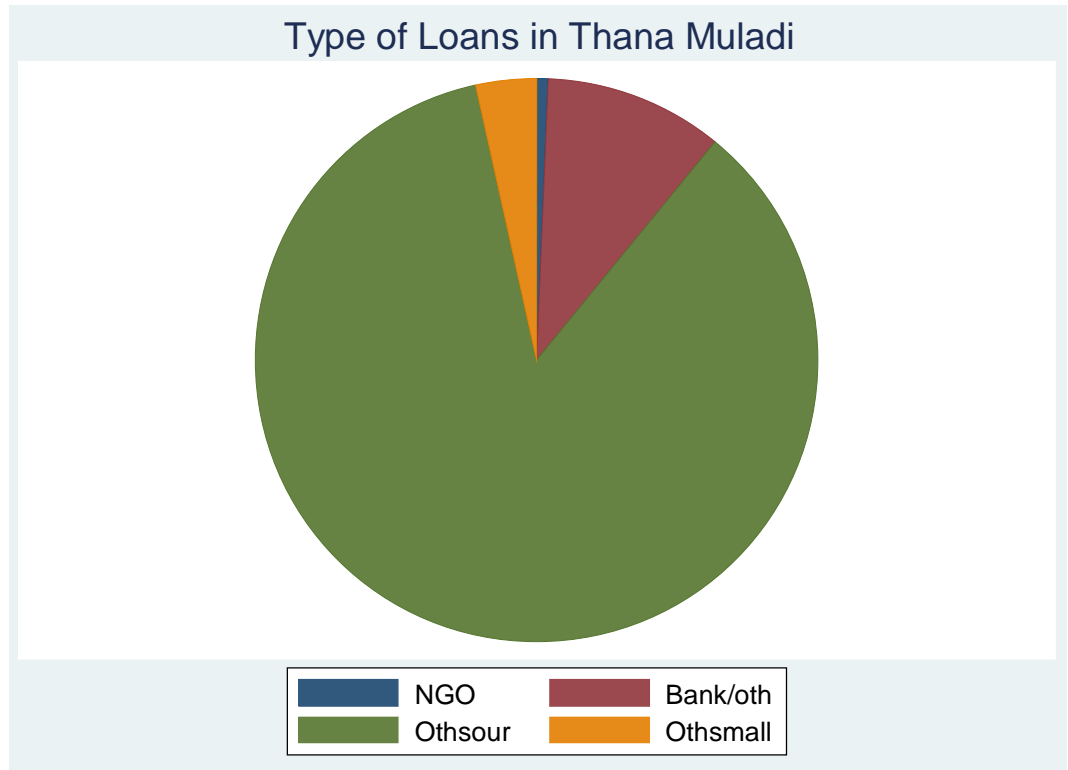


Fig. 1.6

# Type of Loan across *thana*

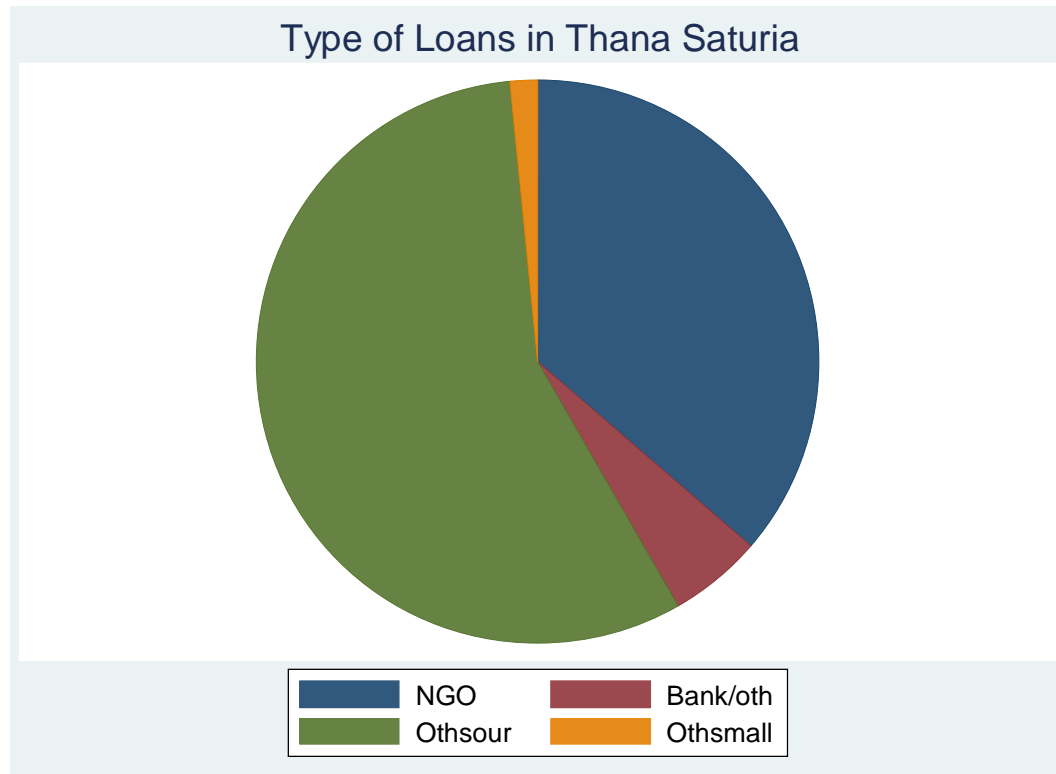


Fig. 1.7

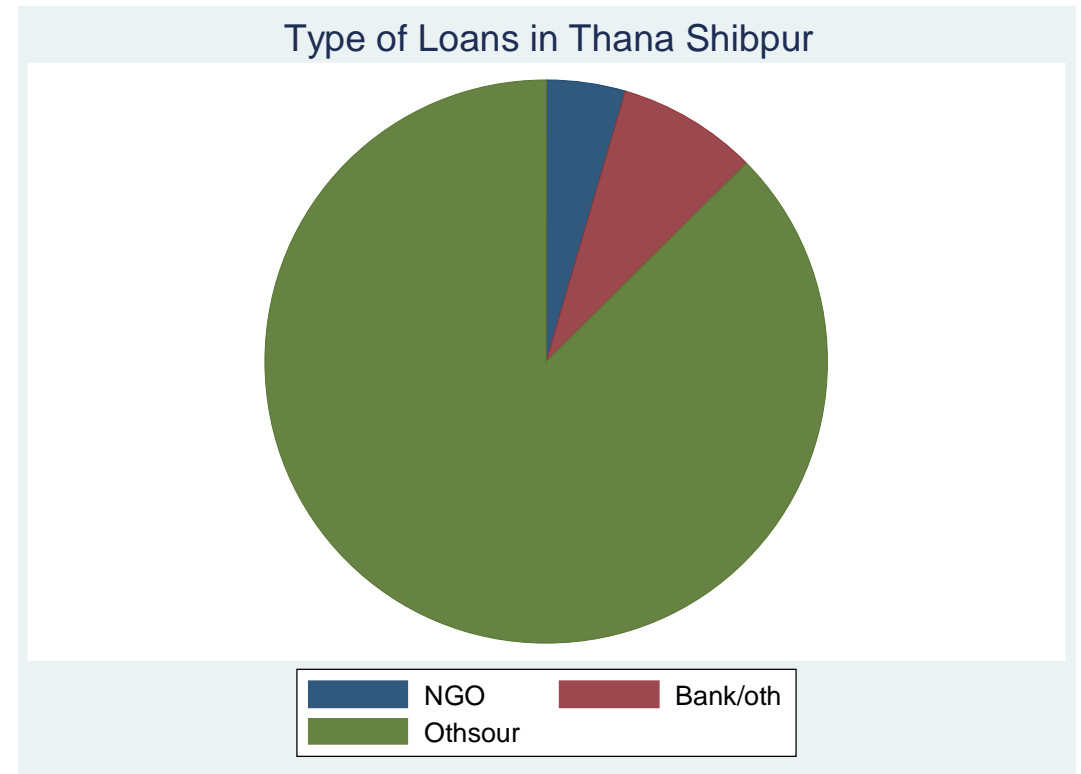


Fig. 1.8

# Type of Loan across *thana*

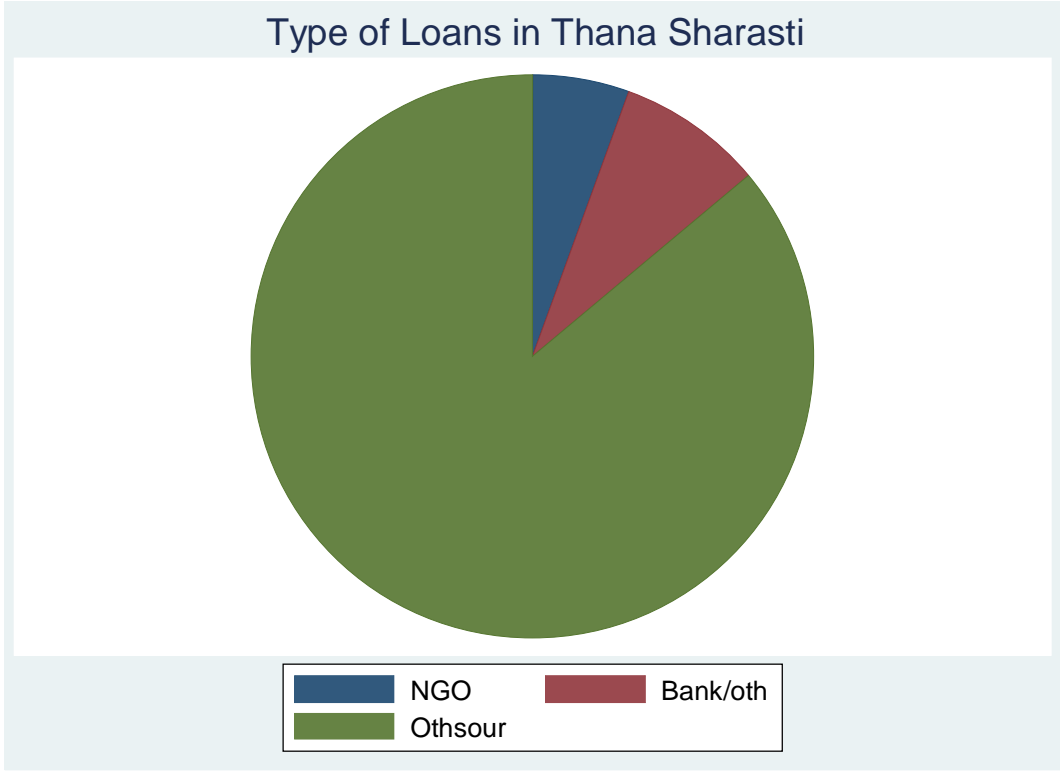


Fig. 1.9

# Credit transaction details across geographical units

Thana	Loans given by Moneylender (in %)	MFI Index	Loan Size (in taka)	Interest rate charged (in %) p.a.
Derai	12.63	0.38	1876.06	88.99
Madaripur	6.38	12.08	3742.91	44.04
Mohamedpur	6.17	8.93	5040.56	21.09
Muladi	34.53	1.06	3452.62	53.65
Saturia	3.74	35.44	4778.01	28.97
Shibpur	2.53	21.41	3085.93	23.94
Sharasti	8.37	9.23	3769.75	36.81

Fig. 1.3

# Thana based MFI Index

loancsh	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
mfindex	48.14111	15.001	3.21	0.001	18.71625	77.56597
_cons	2984.109	238.0041	12.54	0.000	2517.257	3450.96

- MFI index is significant at 5% level of alpha
- The  $R^2$  value is very low (0.0067), but this can be guessed from the fact that the indices do not have very high variance

# Village level MFI Index

loancsh	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
mfivillin	39.01785	10.11014	3.86	0.000	19.18643	58.84927
_cons	3374.206	176.3533	19.13	0.000	3028.283	3720.13

- MFI index is significant at 5% level of alpha
- The  $R^2$  value increased from the previous case of 0.0067 but remains low 0.0098

# Conclusions and Policy Implications

- We find that thanas which faced similar levels of destruction on account of the floods were in fact seeing a drastic difference vis-à-vis the rates of interest charged by the informal credit market
- We try to explain part of this difference by the presence of MFIs in the credit market by showing that higher liquidity due to presence of MFIs leads to lower rates of interest being charged and higher value loans given out
- In fact while focusing on the main category of lenders we observe that for thanas with MFIs, even local money lenders charge a substantially lower rate of interest than they do in other thanas