Microfinance

How to Improve it? & Equilibrium Effects

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Last Time

Borrowers are not monolithic, have heterogeneous goals:

- Credit as a way to finance entrepreneurship
- Credit as a way to consume sooner

Microfinance typically does not attempt to distinguish between these two groups.

- Screening technologies can be expensive
- Homogeneous contracts allow MFIs to economize on costs
- Contracts that limit risk-taking improve repayment

But that might lead MFIs to offer a product that is possibly wrong for everybody

How could financial institutions do better?

What types of products might be better for:

- Gung-ho entrepreneurs
- Reluctant or non- entrepreneurs

One possibility:

- Larger, individual loans for the first group
- Improved savings technologies for the second

MFIs may not have incentives to segment this market (Roth 2017)

Road Map

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    - For Some?
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    - Improved screening?
    - Innovations in product offerings and contract design?
5. Aggregate Impacts of MF

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Prospects for segmenting the market

Is it possible to offer better contracts to the "gung-ho" entrepreneurs?

- Note that doing so makes many of the contractual advantages outlined above disappear

Some hope:

- Screening on business age doesn't seem too hard (long-run study)
- Possibility of improved screening
- MFIs have increasingly been moving toward an individual loan model, graduation

Screening

Standard microfinance contract not designed for much screening

- Outsource some to group
    - Limited evidence that group screens much
- Give homogeneous contracts
- Near perfect repayment, so no need to invest in screening
    - True for MFI and group
- Main costs - loan officers. Asking them to do more screening raises costs. Need different type of worker.

Possibilities:

- Use new data sources + ML
- Use peer information more surgically than current status quo

Bjorkegren and Grissen (2020)

Mobile phones far more prevalent than bank accounts:

- Setting: Middle income country in S. Am
- 34% have bank accts, 89% have mobile phones

Collect mobile phone use data and loan repayment information from telcom

- 5,500 attributes from telco meta-data
- Model with mobile predictors outperforms credit bureau records
- Model with mobile predictors works as well for those with no credit record at all
- "Individuals in the highest quintile of risk by the measure used in this article are 2.8 times more likely to default than those in the lowest quintile"

Bjorkegren and Grissen (2020)

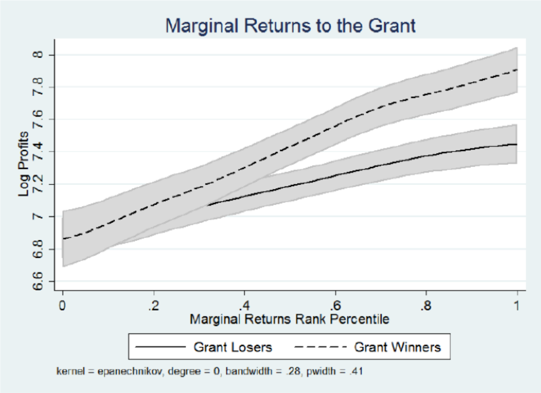
	Correlation with repayment	t-stat	Number of Features
Demographics			**2**
Age	0.073	2.35	
Female	−0.039	−1.26	
Credit bureau			**36**
Has a credit bureau record	−0.022	−1.89	
Summary score (lower is better)	−0.072	−6.15	
Fraction of debt lost	−0.046	−3.86	
Phone usage			**5,541**
Categories	*High-performing example feature:*		
Periodicity	−0.163	−5.27	796
	Text messages by day, ratio of magnitudes of first fundamental frequency to all others		
Slope	0.126	4.06	44
	Slope of daily calls out		
Correlation	0.111	3.57	224
	Correlation in text messages two months ago and duration today		
Variance	−0.104	−3.34	4,005
	Difference between 80^{th} and 50^{th} quantile of text messages use on days texts are used		
Other	0.100	3.07	542
	Number of important geographical location clusters		

What about peer screening?

Natalia Rigol, Ben Roth, and Reshman Hussam investigate this:

- Do individuals have knoweldge about the returns to capital of their peers?
- Context: microentrepreneurs in Amravati, Maharastra India
- Baseline conducted with 1,345 households.
- Organized participants into groups of 5 based on geography
- Invited them to come to a meeting, chance to win a $100 grant
- At meeting, conducted a ranking activity: "who could grow their profits the most if they were to receive the Rs. 6,000 grant"

Figure 3: Marginal Returns to the Grant by Percentile of the Average Community Ranks Distribution



This figure plots the outcome of a local polynomial regression of degree 1. Log profits are measured at followup rounds. 90% confidence bands shown in gray shading.

Powerful proof of concept!

Problem: Peers Might Lie

	(1) All Questions Pooled
Rank	0.162***
	(0.016)
Rank*Stakes	-0.056***
	(0.021)
Average Rank	
Average Rank*Stakes	
Reports	Individual
N	32225
No. Obs	1336

- Dependent variable: entrepreneur true outcomes (income, profits, hours worked etc.)
- Regressor: peer ranks
- Stakes: treatment where peer report used to allocate $
- Problem especially bad for family and close friends (not reported here)

Possible Solutions?

	(1) All Questions Pooled	(2) All Questions Pooled	(3) All Questions Pooled	(4) All Questions Pooled
Average Rank	0.212***	0.158***	0.141***	0.116**
	(0.036)	(0.041)	(0.046)	(0.047)
Average Rank*Public	0.003	0.002	0.166**	0.027
	(0.052)	(0.060)	(0.064)	(0.058)
Average Rank*Incentives	-0.023	-0.079	0.141**	0.142**
	(0.061)	(0.065)	(0.067)	(0.071)
Average Rank*Incentives*Public	-0.025	0.045	-0.243**	-0.118
	(0.091)	(0.098)	(0.094)	(0.098)
Who is Ranked?	Self	Self	Not Self	Not Self
Treatment	[No Stakes]	[Stakes]	[No Stakes]	[Stakes]
N	3241	3297	3254	3310
No. Obs	1330	1330	1336	1336

Authors test 2 possible solutions

- Peers make rankings in public (accountability)
  - No effect under stakes (col 4)
- Peers receive incentives for correct reports
  - Substantial improvement under stakes (col 4)

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- Peers make rankings in public (accountability)
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- Peers receive incentives for correct reports
  - Substantial improvement under stakes (col 4)
- How to implement incentives in practice? Scalable "technology" would likely look quite different (e.g., incentivized referrals as in Bryan, Karlan and Zinman *AEJ:Applied*)

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Scope for getting larger loans to GEs?

Potential for "graduation" model:

- MF generates information about borrowers over the loan cycle
  - Information about business
  - Repayment history
  - Demand for credit
- Idea: take successful borrowers and give them larger, individual liability loans

Bari et al 2021

Authors investigate how to deliver more financing to successful MF clients

- Context:
    - MFI in Pakistan, interest-free loans
    - Larger loans after repayment, up to cap of $\approx \$500$
- New product idea:
    - Hire-purchase (aka Rent to own) contract
    - Borrowing entrepreneur selects asset for biz (e.g., sewing machine
    - Lender approves purchase up to $\approx \$2,000$ (4x cap)
    - Borrower posts 10% down-payment, MFI buys 90%
    - Over 18 months, borrower pays rental fee for use of asset and buys out the MFI's share
    - In case of breach of contract, MFI liquidates asset and splits proceeds by ownership shares

Potential problem: may still be hard to liquidate the asset in low enforcement environments.

- Need to lean heavily on screening here

Bari et al 2021: Experiment

- Sample:
  - 757 borrowers who had successfully repaid at least 1 loan, maxed out at cap
- Treatments
  1. Control: can take interest-free loan at cap $\approx$ \$500
  2. Treatment A: Hire-purchase contract, fixed monthly payment schedule
  3. Treatment B: Hire-purchase contract, option of repayment flexibility, pre-payment
- TA and TB look similar, so I will show pooled results
- Take-up
  1. Control: $\approx 30\%$
  2. Treatment A: $\approx 50\%$
  3. Treatment B: $\approx 50\%$

Bari et al 2021: 2 yr Results

	(1) Runs a buiness	(2) Number of businesses	(3) Business total assets	(4) Business revenue	(5) Business profits	(6) Business employees
Assignment	0.09	0.10	401.22	1.82	26.93	0.04
	(0.02)	(0.02)	(89.94)	(39.65)	(9.93)	(0.06)
	[0.00]***	[0.00]***	[0.00]***	[0.96]	[0.01]***	[0.54]
	{0.00}***	{0.00}***	{0.00}***	{0.47}	{0.01}***	{0.28}
Control mean (follow-up)	0.80	0.82	1003.34	689.65	249.31	0.56
Observations	3,608	3,608	3,608	3,608	3,608	3,608

	(1) Total fixed assets	(2) Current assets: cash	(3) Current assets: accounts receivable	(4) Current assets: inventory
Assignment	438.05	2.68	-0.59	-29.76
	(67.15)	(1.77)	(1.47)	(34.53)
	[0.00]***	[0.13]	[0.69]	[0.39]
	{0.00}***	{0.25}	{0.53}	{0.36}
Control mean (follow-up)	660.19	31.38	9.93	250.77
Observations	3,608	3,608	3,608	3,608

Bari et al 2021: 2 yr Results

	(1) Household income	(2) Household consumption expenditure	(3) Household savings	(4) Household loans	(5) Household assets
Assignment	31.47	12.95	16.44	-22.81	20.33
	(12.66)	(3.37)	(19.16)	(3.65)	(14.03)
	[0.01]**	[0.00]***	[0.39]	[0.00]***	[0.15]
	{0.01}**	{0.00}***	{0.19}	{0.00}***	{0.08}*
Control mean (follow-up)	357.35	220.40	113.03	46.05	681.79
Observations	3,608	3,608	3,608	3,608	1,410

Also, large increase in expenditures on education

Other Design Considerations

Evidence that a set of businesses is credit constrained

- High demand for more microcredit
- Marginal investments have high returns
- $\implies$ benefits from channeling more resources to these businesses

Other limitations in standard microfinance contracts

- Gender: within-household conflicts over resource allocation
  - Recall, women have low returns to capital when HH also has a male-owned business
- Rigidity of microfinance may prevent risk-taking. Profitable, but risky investments may be passed up by borrowers

Intrahousehold Bargaining and Microfinance Returns

Emma Riley asks whether the mode of MF disbursement can lead to more female control over how loan proceeds are spent

- Uganda: sharing rules withing household over *cash*. However, rules not as strong for money in a bank or digital payment account
- RCT with 3000 woman microfinance borrowers
- Treatments
  - Control: Cash disbursement (status quo)
  - Treatment 1: Cash disbursement + mobile account
  - Treatment 2: Mobile disbursement + mobile account

Mobile Disbursement Results

Results 8 months post disbursement:

	(1) profit	(2) savings	(3) capital
Mobile account	10.41	3.33	38.27
	(13.01)	(34.35)	(76.19)
	[0.99]	[0.99]	[0.99]
Mobile disburse	63.72***	30.44	254.59***
	(12.73)	(36.82)	(74.51)
	[0.00]	[0.74]	[0.01]
Observations	2,639	2,639	2,639
R-squared	0.44	0.35	0.51
Control mean endline	395.3	559.2	2375
Control mean baseline	419.8	483.6	2297
p-value T1=T2	0.00	0.50	0.00

- Mobile money disbursement increased profits by 15% and business capital by 11%
- Large impacts!
- Shows there is much room for improvement relative to standard contract (cash)
- Conventional microfinance not reaching full possibilities

Tweaking the Contract Structure to Allow for Risk-Taking

Field, Pande, Papp, and Rigol's idea: Make MF slightly less rigid

- Recall that microfinance contracts are rigid, and groups might self-police to limit risk
- May lead to MF being used to finance low return, low risk investments
- RCT:
  - Control Group: Status quo of weekly payments
  - Treatment Group: Grace period of 1 month before first payment due

Grace Periods and Profits

Table 2—Impact of Grace Period on Long-Run Profit, Income, and Capital

	Average weekly profits		log of monthly HH income		Capital	
	OLS (no controls) (1)	OLS (with controls) (2)	OLS (no controls) (3)	OLS (with controls) (4)	OLS (no controls) (5)	OLS (with controls) (6)
Panel A. Full sample						
Grace period	906.6**	902.9**	0.195**	0.199**	28,770.2**	35,733.1***
	(373.8)	(370.2)	(0.0805)	(0.0782)	(11,291.0)	(13,020.6)
Observations	752	752	749	749	766	766
Control mean	1,586.8	1,586.8	20,172.71	20,172.71	35,730.2	35,730.2
	(121.8)	(121.8)	(55,972.25)	(55,972.25)	(5,056.0)	(5,056.0)

Grace Periods and Default

TABLE 3—IMPACT OF GRACE PERIOD ON DEFAULT

	Full loan not repaid				
	Within 8 weeks of due date (1)	Within 24 weeks of due date (2)	Within 52 weeks of due date (3)	Amount outstanding within 52 weeks of due date (4)	Repaid at least 50 percent of the loan (5)
Panel A. (No controls)					
Grace period	0.0901**	0.0696**	0.0614**	148.7*	−0.0137
	(0.0349)	(0.0280)	(0.0251)	(83.61)	(0.0151)
Panel B. (With controls)					
Grace period	0.0845**	0.0642**	0.0609**	149.0*	−0.0156
	(0.0333)	(0.0262)	(0.0249)	(83.55)	(0.0159)
Observations	845	845	845	845	845
Control mean	0.0424	0.0212	0.0165	69.65	0.988
	(0.0142)	(0.0101)	(0.00899)	(40.15)	(0.00774)

MFI not willing to tolerate extra default, abandoned grace period

- Very hard politically to raise interest rates to accommodate more default

Grace Periods v2

Battaglia, Gulesci and Madestam propose an even more flexible contract in Bangladesh

- Can choose 2 monthly installments to skip (delay)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Business owner	Business assets	Number of workers	Business hours	Owner's hours worked	Revenues (annual)	Costs (annual)	Profits (annual)	Profits (month)	Range of revenues	Aggregate index
						Panel A: ***Dabi***					
Treatment	0.026	1881.254**	0.172	127.789	71.219	28153.189***	24392.605***	1087.586	96.576*	2801.612**	0.183**
	(0.025)	(926.570)	(0.326)	(83.059)	(69.523)	(8716.036)	(8099.027)	(651.456)	(56.069)	(1215.694)	(0.079)
	[0.391]	[0.081]	[0.682]	[0.214]	[0.391]	[0.002]	[0.005]	[0.189]	[0.182]	[0.064]	[0.054]
Observations	2087	2086	2087	2087	2087	2087	2087	2087	2087	2087	2087
Mean in control	0.549	3685.413	1.091	1577.286	1474.800	32561.844	26870.630	4275.948	358.718	2647.696	-0.000

Similar impacts on biz outcomes

Grace Periods v2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Borrower no longer	Classified	Loan not fully paid		Full loan not repaid within		
	with BRAC	as "Default"	in 12 months	by the end of the loan cycle	2 months	6 months	12 months
					after the end of the loan cycle		
			Panel A: *Dabi*				
Treatment	-0.068*	-0.017**	0.082***	-0.064***	-0.018	-0.019	-0.019
	(0.036)	(0.008)	(0.025)	(0.017)	(0.013)	(0.013)	(0.013)
	[0.152]	[0.095]	[0.007]	[0.001]	[0.269]	[0.217]	[0.218]
Observations	945	945	914	914	914	914	914
Mean in control	0.371	0.048	0.109	0.109	0.046	0.042	0.040

- No evidence of increased default.
- Grace periods later in loan cycle help to modestly *decrease* default

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   - Impacts of MF in General Equilibrium
   - Interplay between formal and informal credit

How Does Microfinance Aggregate Up?

Preface to AEJ Applied Jan 2015 microfinance issue:

> *We have only scratched the surface of identifying spillover and general equilibrium effects ... Nonborrowing wage earners could benefit from increased employment opportunities (Banerjee et al 2015)*

How can access to (micro) credit affect the broader economy?

1. facilitate entrepreneurship and job creation (e.g., Evans and Jovanovic 1989, Banerjee and Newman 1993)
   - $\Rightarrow$ *Business finance channel*
2. allow households to bring consumption forward in time
   - may $\rightarrow$ increased demand for firms selling to these borrowers
   - $\Rightarrow$ *Aggregate demand channel*

Microfinance targeted to *rural* villagers and microenterprises; looks different from bank capital, prior macro-finance work. Multipliers may be higher given liquidity constraints.

Motivation: Breza and Kinnan 2021

Goal: Measure the impacts of microcredit on the labor market (wages specifically)

Fully quantifying these effects requires *market-level* variation in access to microcredit:

- need a quantitatively large, exogenous shock to credit access
- *also* need the shock to play out at the level of entire labor markets

We explore the equilibrium impacts of reduced microcredit access in rural India, using the AP crisis as a natural experiment

- wiped approx. $1 billion out of the Indian microcredit market
- district-level differences in exposure create quasi-exogenous, market-level variation

The AP Crisis

In the months following the ordinance, a very large fraction of borrowers in AP defaulted on their loans.

- Effects on borrowers *within* AP
  - loan forgiveness (implicit)
  - no future access to credit
- Effects on borrowers *outside* AP
  - No similar laws elsewhere
  - No loan forgiveness – borrowers kept repaying

To isolate effects of reduction in credit access we focus on the effects *outside of AP*

Press Coverage: Economic Times

Microfinance Crisis: MFIs with sizeable presence in Andhra Pradesh on the brink of closure

John Samuel Raja D & M Rajshekhar, ET Bureau Jan 13, 2011, 01.06am IST

Heterogeneity in size of credit contraction outside of AP

- A district where the major MFI was heavily exposed to AP before 2010 faced a larger credit contraction
- A district where the major MFI was not exposed to AP before 2010 faced a smaller credit contraction

Empirical Idea: compare districts with low vs. high exposure to AP, before and after the ordinance – differences - in - differences!

Empirical Strategy: Diff in Diff

Data:

- District-level lending panel data from 25 MFIs to construct "instrument"
- NSS data to measure outcomes

First Stage:

- $\frac{GLP_{dt}}{n_{dt}} = \alpha + \delta_t + \delta_d + \beta \times Exposure_d \times Post_t + X'_{dt}\gamma + \varepsilon_{dt}$

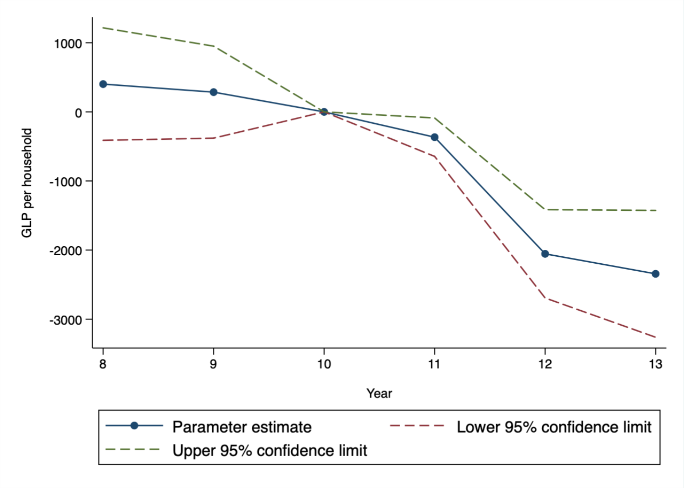
Reduced Form:

- $y_{idt} = \alpha + \delta_t + \delta_d + \beta \times Exposure_d \times Post_t + X'_{idt}\gamma + \varepsilon_{idt}$

Controls X'_{idt}

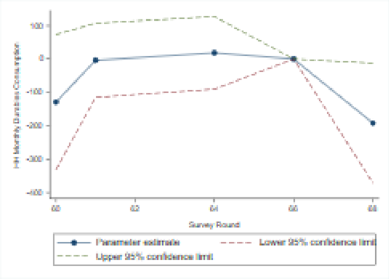
- calendar month when survey was conducted; household size; rural population of the district at t (and its square); dummy for the presence of microfinance in the district in 2008 and 2010 $\times$ round; dummies for quartiles of 2008, 2010 gross loan portfolio, $\times$ round; district population and population squared in 2010 $\times$ round; distance to AP $\times$ round; baseline district-level consumption and wages $\times$ round

Change in Principal Outstanding: High vs. Low Exposure Districts

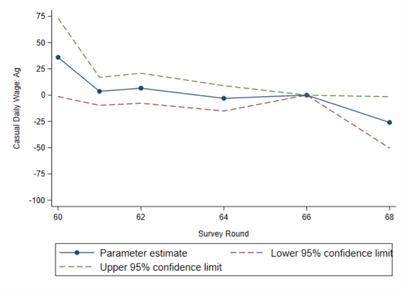


- No difference in credit growth trajectory pre-ordinance
- Large widening of credit outstanding post-ordinance

Pre-trends Plots: Key Outcomes



(a) Consumption - Durables



(b) Average Wages

- Include extra rounds back to 2004
- No significant differences before the crisis
- Round 60 (2004) "thin"

Cross-Sectional, Representative Credit Data: NSS 70

Table: Exposure to the AP Crisis and total MFI lending

	(1) District gross loan portfolio per household (balance sheet)	(2) MFI amt outstanding,	(3) Bank amt outstanding,	(4) Total loan amt outstanding,	(5) MFI amt outstanding, log.	(6) Bank amt outstanding, log.	(7) Total loan amt outstanding, log.
Any exposed lender × Post 2010	-324.631***	-1296.836***	-815.937	-3286.771	-0.634***	0.123	-0.773**
	(50.480)	(389.146)	(1898.591)	(3004.950)	(0.159)	(0.244)	(0.374)
Exposure Ratio × Post 2010	-170.985***	-626.543***	465.688	-1069.412	-0.331***	0.063	-0.355*
	(23.703)	(185.490)	(901.626)	(1398.391)	(0.067)	(0.115)	(0.195)
Control mean	423.496	2394.640	29531.260	69353.672	-5.360	-2.641	5.476
Control SD	546.901	13200.690	104467.426	142601.618	4.836	7.641	8.028
Observations	1048	33559	33559	33559	33559	33559	33559

- Balance sheet (col 1) and NSS 70 (cols 2 to 5) both show large falls in microcredit.
  - Patterns not driven by selection of relatively bad MFIs in exposed districts in MFIN data.
- No evidence banks were able to step into the void (cols 3, 6). Total credit falls (col 7)

Average Treatment Effects: Labor

Table: Labor Outcomes

	(1) Casual Daily Wage	(2) HH Weekly Total Days Worked	(3) HH Weekly Casual Days Worked	(4) HH Weekly Labor Earnings	(5) Any HH Member Invol Unemployed
Any exposed lender $\times$ Post 2010	-6.432**	0.057	-0.446**	-86.227***	0.012
	(2.954)	(0.234)	(0.196)	(30.333)	(0.011)
Exposure Ratio $\times$ Post 2010	-3.439**	-0.063	-0.154*	-44.836***	0.002
	(1.335)	(0.111)	(0.089)	(14.181)	(0.005)
Control mean	153.361	10.275	3.455	836.465	0.098
Control SD	87.097	6.738	5.134	1266.456	0.297
Observations	40584	119668	119668	119668	119668

- Decrease in wages and total HH labor earnings
- No treatment effect on total days worked
- Decrease in casual labor days worked

Average Treatment Effects: Consumption

Table: Consumption Outcomes

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Nondurables	(3) HH Monthly Consumption: Durables	(4) Below Proverty Line
Any exposed lender × Post 2010	-138.218	-89.202	-41.714**	0.000
	(118.719)	(106.911)	(16.737)	(0.021)
Exposure Ratio × Post 2010	-151.222***	-127.775***	-17.130**	0.010
	(51.919)	(46.950)	(7.502)	(0.010)
Control mean	5502.140	5183.746	284.541	0.254
Control SD	3433.515	2977.998	665.044	0.435
Observations	111692	119668	111692	111692

- Decrease in durable and non-durable consumption
- Implied back-of-the-envelope multiplier: 2.9 (consistent with Kenya cash transfer evidence)
- No effect on poverty headcount ratios

Aggregate Demand? Wages

Aggregate demand channel $\Rightarrow$ wage effect for non-tradables should be smaller than tradables

Table: Casual Daily Wages by Sector

	(1) Casual Daily Wage: Pooled	(2) Casual Daily Wage: Men	(3) Casual Daily Wage: Winsorized	(4) Casual Daily Wage: Men, Win.
(Any exposed lender x Post 2010) x Agriculture	-5.081	-4.231	-5.555*	-4.887
	(3.340)	(3.732)	(3.173)	(3.478)
(Any exposed lender x Post 2010) x Non-agriculture	-9.436**	-9.194*	-7.949*	-7.819*
	(4.380)	(4.810)	(4.084)	(4.455)
p-value: Ag=non-Ag	0.304	0.276	0.551	0.497
(Exposure Ratio x Post 2010) x Agriculture	-2.342	-1.737	-2.802**	-2.365
	(1.469)	(1.665)	(1.386)	(1.550)
(Exposure Ratio x Post 2010) x Non-agriculture	-5.315**	-5.072**	-4.803**	-4.680**
	(2.209)	(2.487)	(2.045)	(2.279)
p-value: Ag=non-Ag	0.155	0.150	0.311	0.290
Ag mean	128.581	140.534	128.211	140.068
Non-ag mean	184.242	194.709	178.099	187.703
Observations	40584	29493	40584	29493

Investment: NSS 70 data

Table: Exposure to the AP Crisis and Investment: NSS round 70 data

	(1) Total Investment	(2) Home Improvements	(3) Ag. Business Investment	(4) Non-Ag Business Investment
Any exposed lender $\times$ Post 2010	-1134.137*	-889.759*	-31.508	-39.155
	(629.364)	(474.631)	(148.675)	(25.297)
Exposure Ratio $\times$ Post 2010	-719.334**	-412.223*	-51.892	-36.517***
	(286.876)	(222.258)	(69.236)	(11.716)
Control mean	6072.643	3759.068	928.797	187.458
Control SD	25836.638	19110.354	4522.611	977.247
Observations	33559	33559	33559	33559

- significant declines in total investment (col 1)
- largest fall in home construction and home improvements (col 2)
- consistent with aggregate demand channel: most construction inputs are nontradable

What have we learned about Microfinance?

RCT evidence points to modest benefits to borrowers on average:

- Many high-quality experiments from a range of settings
- But this masks substantial heterogeneity:
  - Subset of entrepreneurs use microfinance for meaningful, sustained business growth
  - Other households use loans for consumption, or starting low productivity businesses

The departure of microfinance moves the rural economy.

- Looking only at borrowers misses part of the story
- Shows the importance of well-conceived regulation

Ways to make microfinance more valuable:

- Graduating successful borrowers/businesses into larger loans
- Better screening
- Better suitability to needs of women, HH dynamics
- More flexibility in the contract structure (more equity-like?)

Need for active regulation

Road Map

1. What is Microfinance?
2. How Does Microfinance Work?
3. Does Microfinance Work:
   - For Everybody?
   - For Some?
4. How to Improve Microfinance?
5. Aggregate Impacts of MF
   - Impacts of MF in General Equilibrium
   - Interplay between formal and informal credit

Partial equilibrium network change

- The effect of microfinance on networks of participants
- Microfinance practice forces group participants to spend lots of time with each other
- Does this change networks?

Feigenberg, Field and Pande 2013

The authors randomized groups into monthly vs. weekly meetings (we saw the repayment effects before)

- Recall: No impact of repayment frequency or meeting frequency on repayment in the first loan cycle.
- Reverted back to same contract structure for subsequent loan cycles

Table 2. Meeting Frequency and Social Interactions in the Short Run and Long Run

	Short Run	Long Run			
	Social Contact Index	Total Times Met	Attend Durga Puja	Talk Family	Social Contact Index
	(1)	(2)	(3)	(4)	(5)
Panel A: No Controls					
Treatment 1	2.661***	2.085**	0.070*	0.071*	0.176**
(Weekly-Weekly)	(0.112)	(1.016)	(0.039)	(0.039)	(0.076)
Panel B: Controls Included					
Treatment 1	2.695***	2.078**	0.080**	0.069**	0.184***
(Weekly-Weekly)	(0.102)	(0.909)	(0.038)	(0.035)	(0.068)
Control Mean		5.459	0.152	0.229	
(Monthly-Monthly)		[10.375]	[0.359]	[0.420]	
Specification	OLS	OLS	Probit	Probit	OLS
N	683	3034	3034	3034	3034

Feigenberg, Field and Pande 2013

Supplemental Exercise conducted 16 months after end of 1st loan cycle

- Each person entered into a promotional lottery for MFI's retail store
- Initial ticket - 1 in 11 chance of winning a voucher
- Each person also allowed to give additional tickets to members of the first cycle group, but comes at cost to own odds
  - Altruism
  - Risk pooling
- Randomize *divisibility of the prize* to separate between motives

Feigenberg, Field and Pande 2013

Table 3. Meeting Frequency and Risk-Sharing: Ticket-Giving and Tra

	Main Lottery					Supplementary Lottery
	Gave Ticket					
	All	1-Rs. 200 Voucher	4-Rs. 50 Vouchers			All
			All	Weekly	Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Treatment 1	0.067**	0.043	0.091*			-0.006
(Weekly-Weekly)	(0.034)	(0.041)	(0.048)			(0.071)
Surveyed Second				0.039	0.077	
				(0.073)	(0.061)	
Other Pair Member Gave				0.050	0.212***	
				(0.090)	(0.071)	
Surveyed Second*Other Pair Member Gave				0.158**	0.012	
				(0.067)	(0.060)	
Group Member						0.106***
						(0.038)
Treatment 1*Group Member						0.132*
						(0.074)

Also find less default in subsequent loan cycles – argue that social capital improved risk sharing

General equilibrium network change

- Networks are used to facilitate informal credit markets
- Introduction of formal credit can affect participation in the informal borrowing networks
- Those who take-up have less need to borrow from others,
- ... but have the capacity to re-lend.
- How should we think about the effects of an introduction of formal credit on the informal network?
- What does such an intervention teach us about the nature of network formation and how we should model it?

Table 1B. Endline 1 and 2 summary statistics (control group

	(1)	(2)	(3)
	EL1 Control Group		
	Obs	Mean	St. Dev.
Household composition			
# members	3,264	5.645	(2.152)
# adults (>=16 years old)	3,264	3.887	(1.754)
# children (<16 years old)	3,264	1.738	(1.310)
Male head	3,261	0.894	(0.308)
Head's age	3,257	41.143	(10.223)
Head with no education	3,256	0.311	(0.463)
Access to credit:			
Loan from Spandana	3,247	0.051	(0.219)
Loan from other MFI	3,183	0.149	(0.356)
Loan from a Bank	3,247	0.079	(0.270)
Informal loan	3,247	0.761	(0.427)
Any type of loan	3,264	0.887	(0.317)

What does credit market look like in absence of a lot of microcredit?

Formal Finance when Informal Finance is Already There

Vibrant informal market for loans in developing countries:

- Moneylenders
- Family and risk sharing network
- Trade credit

How do new sources of formal credit interact with existing informal sources?

- Is microfinance improving financial inclusion? Are people gaining access to credit who would otherwise be unbanked?
- OR, is microfinance simply lowering the cost of credit (interest rate) without expanding overall credit access?

Important question because financial inclusion policy often enacted through preferential lending and subsidies

Banerjee, Breza, Chandrasekhar, Duflo, Kinnan and Jackson (2022)

We combine data from two "experiments"

- "Diffusion of Microfinance" natural experiment:
  - Some villages added microfinance (post-network survey)
  - 43 out of 75 (not random)
  - Collected a second snapshot of the network in all of the 75 villages 5-6 years later
- Hyderabad MF RCT

Goal: How does network change because of microfinance? Are there GE impacts, even for those who aren't interested/eligible for MF?

- Karnataka: Diff-in-Diff with panel of full network data (T=2)
- Hyderabad: RCT with cross section of partial network data (can construct full network map using ARD method)

Network-Level Analysis: Karnataka

	(1) Density	(2) Density	(3) Density	(4) Clustering	(5) Clustering	(6) Clustering	(7) Closeness
Microfinance × Post	-0.0119	-0.0128	-0.0128	0.00357	0.00968	0.00968	-0.0225
	(0.00678)	(0.00690)	(0.00716)	(0.0146)	(0.0147)	(0.0153)	(0.00970)
	[0.0836]	[0.0669]	[0.0769]	[0.807]	[0.513]	[0.528]	[0.0234]
Microfinance	-0.0205	0.00477	0.00204	-0.0408	-0.0179	-0.00638	-0.0129
	(0.00842)	(0.00555)	(0.00227)	(0.0159)	(0.0148)	(0.00551)	(0.00993)
	[0.0175]	[0.393]	[0.373]	[0.0123]	[0.230]	[0.250]	[0.199]
Post	-0.0117	-0.0145	-0.0145	-0.00913	0.00852	0.00852	0.105
	(0.00576)	(0.0107)	(0.0111)	(0.0100)	(0.0249)	(0.0258)	(0.00762)
	[0.0454]	[0.182]	[0.198]	[0.366]	[0.733]	[0.742]	[0]
Observations	150	150	150	150	150	150	150
Double-Post LASSO		✓	✓		✓	✓	
Village FE			✓			✓	
Non MF Mean	0.1135	0.1135	0.1135	0.329	0.329	0.329	0.431
Depvar Mean	0.0983	0.0983	0.0983	0.307	0.307	0.307	0.418

- % of other households one is connected to (density) declines
- similar pattern in Hyderabad (unreported here)
- suggestive (noisy) evidence that avg. distances to other households declines (closeness $= 1/\text{distance}$)

Link-Level Analysis

- Identify which households would tend to have gotten loans in non-MF villages/neighborhoods
- Use predictors of access to microfinance in a random forest model
- Allows authors to compare likely loan takers/non takers across MF and non-MF areas
- Two types of households: H and L
- Different in multiple respects: e.g. (Karnataka: H are slightly poorer, more connected)
- how does microfinance exposure affect the formation of links across types (H and L) of households?
    - LL, LH, HH denote link by type pairs

Link-Level Analysis: Karnataka

	(1) Linked Post-MF	(2) Linked Post-MF	(3) Linked Post-MF	(4) Linked Post-MF
Microfinance	-0.058	-0.059	-0.023	-0.021
	(0.018)	(0.019)	(0.008)	(0.008)
	[0.002]	[0.002]	[0.006]	[0.008]
Microfinance $\times$ *LH*	0.009	0.001	0.007	0.007
	(0.015)	(0.014)	(0.004)	(0.004)
	[0.573]	[0.935]	[0.120]	[0.109]
Microfinance $\times$ *HH*	0.039	0.023	0.009	0.012
	(0.022)	(0.022)	(0.007)	(0.007)
	[0.086]	[0.292]	[0.206]	[0.059]
Observations	57,376	57,376	846,561	846,561
Linked Pre-MF	Yes	Yes	No	No
Controls		✓		✓
Depvar Mean	0.441	0.441	0.0636	0.0636
LL, Non-MF Mean	0.482	0.482	0.0753	0.0753
MF + MF x *LH* = 0 p-val	0.014	0.005	0.015	0.014
MF + MF x *HH* = 0 p-val	0.361	0.088	0.101	0.232
MF + *LH* x MF = MF + *HH* x MF p-val	0.137	0.286	0.641	0.245

Link-Level Analysis: Hyderabad

	(1) Prob. Linked	(2) Prob. Linked
Microfinance	−0.005	−0.007
	(0.002)	(0.002)
	[0.035]	[0.004]
Microfinance x *LH*	0.002	−0.001
	(0.003)	(0.002)
	[0.577]	[0.764]
Microfinance x *HH*	−0.011	−0.007
	(0.008)	(0.006)
	[0.203]	[0.281]
Observations	141,996	141,996
Controls	No	Yes
Depvar Mean	0.0255	0.0255
LL, Non MF Mean	0.0268	0.0268
MF + MF x *LH* = 0 p-val	0.387	0.019
MF + MF x *HH* = 0 p-val	0.066	0.041
MF + MF x *HH* = MF + MF x *LH* p-val	0.038	0.18

- Recall: not a panel, so cannot condition on pre-links

Triads of Nodes: Karnataka

	(1) Full triangle linked Post-MF	(2) Full triangle linked Post-MF	(3) Any link in triangle survived Post-MF	(4) Any link in triangle survived Post-MF
Microfinance	−0.078	−0.070	−0.085	−0.076
	(0.029)	(0.026)	(0.023)	(0.019)
	[0.008]	[0.008]	[0.000]	[0.000]
Microfinance × *LLH*	0.026	0.015	0.043	0.029
	(0.021)	(0.019)	(0.018)	(0.015)
	[0.228]	[0.437]	[0.015]	[0.050]
Microfinance × *LHH*	0.054	0.028	0.057	0.031
	(0.030)	(0.025)	(0.025)	(0.018)
	[0.072]	[0.256]	[0.022]	[0.092]
Microfinance × *HHH*	0.093	0.049	0.087	0.048
	(0.042)	(0.038)	(0.031)	(0.026)
	[0.028]	[0.199]	[0.006]	[0.061]
Observations	53,233	53,233	53,233	53,233
Linked Pre-MF	Yes	Yes	Yes	Yes
Controls		✓		✓
Depvar Mean	0.197	0.197	0.808	0.808
LLL, Non-MF Mean	0.252	0.252	0.864	0.864
MF + MF x *HHH* = 0 p-val	0.698	0.549	0.935	0.209
MF + MF x *LLH* = 0 p-val	0.023	0.03	0.022	0.025
MF + MF x *LHH* = 0 p-val	0.262	0.048	0.141	0.018
MF + MF x *HHH* = MF + MF x *LLH* p-val	0.076	0.35	0.093	0.459
MF + MF x *HHH* = MF + MF x *LHH* p-val	0.212	0.492	0.075	0.307
MF + MF x *LLH*= MF + MF x *LHH* p-val	0.122	0.456	0.409	0.934

- *LLL* fall by *more* than other configurations of nodes

Triads of Nodes: Hyderabad

All variables x 1000	Full Triangle Linked	Full Triangle Linked
	(1)	(2)
Microfinance	−0.018	−0.034
	(0.010)	(0.020)
	[0.067]	[0.086]
Microfinance × LLH	0.010	−0.012
	(0.011)	(0.013)
	[0.370]	[0.344]
Microfinance × LHH	−0.027	−0.052
	(0.038)	(0.040)
	[0.472]	[0.191]
Microfinance × HHH	−0.177	−0.132
	(0.097)	(0.089)
	[0.067]	[0.139]
Observations	3,341,006	3,341,006
Controls	No	Yes
Depvar Mean	0.0353	0.0353
LLL, Non-MF Mean	0.0359	0.0359
MF + MF × HHH = 0 p-val	0.045	0.087
MF + MF × LLH = 0 p-val	0.552	0.064
MF + MF × LHH = 0 p-val	0.256	0.072
MF + MF × HHH = MF + MF × LLH p-val	0.046	0.144
MF + MF × HHH = MF + MF × LHH p-val	0.041	0.162
MF + MF × LLH = MF + MF × LHH p-val	0.217	0.178

- Results noisier: LLL falls comparably to LLH, HHH falls most.

Interpretation

Summary of results:

- On average, microfinance thins out the network (can see it in both settings)
- H types see much smaller effects
- L types see large effects
- LLL triangles have the *comparable* impacts

For the LL links to see the biggest impacts, it must be the case that *global* spillovers matter

- LL not falling because part of LLH triangle (as would be the case in Jackson et al "Social quilts" model)
- Propose a model where individuals must pay an effort cost to form and maintain links.
- The effort cost is time spent socializing in the "town square"
- So if returns to one type of link go down, overall effort decreases, leading to a decrease in *all* types of relationships

Impact of MF on Borrowing (K)

	(1) MFI	(2) Friends	(3) SHG	(4) Moneylender	(5) Family
Microfinance $\times$ Post	476.572	-562.308	-844.524	704.391	677.970
	(148.808)	(330.341)	(384.839)	(800.168)	(659.590)
	[0.002]	[0.089]	[0.029]	[0.379]	[0.305]
Microfinance $\times$ Post $\times$ H	1,795.233	203.926	48.466	$-2,210.964$	$-1,608.814$
	(245.414)	(242.383)	(346.884)	(943.562)	(1,185.489)
	[0.000]	[0.401]	[0.889]	[0.020]	[0.175]
Observations	28,062	27,194	28,062	28,062	28,062
Depvar Mean	596.976	860.228	1863.324	2667.56	1656.881
L, Non-MF Mean	189.671	1148.705	1920.918	2344.905	1711.001
MF x Post x H + MF x Post =0 p-val	0.000	0.255	0.119	0.084	0.325

- Decline in borrowing from friends and SHGs for L types
- No change for H types
- Large impact on microfinance borrowing for H (validates RF)

Impact of MF on Borrowing (H)

	(1) MFI	(2) Friends	(3) SHG	(4) Moneylender	(5) Family
Microfinance	−209.748	86.742	−1,882.840	−2,664.192	−256.318
	(235.127)	(894.331)	(801.110)	(1,455.603)	(656.431)
	[0.375]	[0.923]	[0.021]	[0.071]	[0.697]
Microfinance × H	8,312.670	−637.232	−1,577.128	4,689.554	1,796.860
	(448.982)	(1,491.449)	(1,369.064)	(2,622.331)	(1,366.622)
	[0.000]	[0.671]	[0.252]	[0.077]	[0.192]
Observations	6,811	6,863	6,863	6,863	6,863
Depvar Mean	3107.86	7895.05	6935.66	18805.06	2620.97
L, Non MF Mean	2091.75	8110.94	7064.44	19601.47	2704.03
MF + MF × H = 0 p-val	0.000	0.664	0.012	0.426	0.245

- Differential microfinance borrowing validates RF classifier
- Large declines in informal borrowing for L types

Measuring Insurance Value

Recall "Townsend Regression" (Townsend, 1994)

$$c_{ivt} = \alpha + \beta y_{ivt} + \mu_{vt} + \epsilon_{ivt}$$

- Under full insurance $\beta = 0$.
- More generally $\mathrm{corr}(c_i, y_i | C_v) = 0$.

Treatment interactions

$$\begin{aligned} c_{ivt} = {} & \alpha + \beta_1 y_{ivt} + \beta_2 y_{ivt} \times \mathrm{Treatment}_v \\ & + \beta_3 H_i \times y_{ivt} + \beta_4 y_{ivt} \times H_i \times \mathrm{Treatment}_v \\ & + \tau H_i \times \mathrm{Treatment} + \gamma H_i + \delta \mathrm{Treatment}_v + \mu_{vt} + \epsilon_{ivt} \end{aligned}$$

- $\beta_2 > 0$: *increase* in income-consumption correlation for *L*s when network gets credit access

Ls lose consumption smoothing

	(1) Expenditures: Non-Food	(2) Expenditures: Total
Microfinance×Income	0.071	0.066
	(0.030)	(0.037)
	[0.022]	[0.079]
Microfinance×Income×H	−0.065	−0.112
	(0.044)	(0.058)
	[0.153]	[0.070]
Household Income pc	0.058	0.109
	(0.019)	(0.024)
	[0.004]	[0.000]
Household Income pc ×H	0.020	0.076
	(0.025)	(0.043)
	[0.438]	[0.082]
Observations	10,502	10,590
Depvar Mean	1193	2040
L, Non-MF Depvar Mean	1187	2049
Income Mean	1440	1437
L, Non-MF Income Mean	1437	1435
Test: MF x Inc + MF x Inc x H	0.834	0.407

- Goal: If Ls lose links, do they also lose insurance?
  - Is c_i more correlated with y_i with MF?
  - Use Hyderabad endline consumption, income data
- Townsend 1994-type reg of consumption on:
  - own income
  - treatment
  - H type (w/ interactions)
- Finding:
  - Ls experience a relative increase in corr(c_i, y_i)
  - Hs experience no change
  - L income unaffected by MF (unreported)

Network Chage: Conclusions

- In PE, microfinance forges relationships among group-mates
- But, formal and informal finance are substitutes
- Informal relationships crowded out even for non-borrowing households
- Important policy externality that also needs to be taken into consideration
- For example, subsidize entry of formal insurance with formal credit