14.771: Credit Lecture 2

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Microfinance

- Microfinance
  - History of microfinance
  - Impact of microfinance (overall and heterogeneity)
  - Role of particular microfinance institutions

Microfinance History

- In 1976, Mohammed Yunus created the Grameen Bank: an institution which made small loans to poor women.
- Microcredit has expanded as a worldwide phenomenon:
  - Today, $25 billion outstanding, 150-200 million clients; high repayment rates.
  - Many microfinance institutions are profitable. Some are very profitable.
- Mohammed Yunus and the Grameen Bank won the Nobel Peace Prize.
- Microfinance institutions try to also provide a broader set of financial services, beyond traditional group lending: larger individual loans; savings; insurance.

The Impact of Microcredit

- What question would you want to ask if you wanted to evaluate microcredit?
- Would you even need to evaluate it?
- Why is it challenging?
- For a long time, microcredit organizations refused to ask the question of impact.
- The reasoning was as follows. Since we are profitable, we are like any other business: As long as we have clients, they must get some value out of coming back, and since we don't require any funding, we don't need to be accountable to anyone but the clients.

The Necessity to Evaluate Impacts

- There are two flaws in this reasoning:
- First, while there are some profitable microcredit organizations, many are not, in particular when they lend to the very poorest. There are also hidden subsidies (salaries, funds to start up, etc.). While some venture capitalists make money by lending to microcredit organizations, as an industry, microfinance receives considerable subsidies.
  - Spending resources to lend to the poor is not a problem. We just need to be sure that benefits are higher than costs.
- Second, many now realize that the fact that clients borrow from microfinance organizations does not mean that this is good for them. Poor information, bounded rationality, may lead some clients to fall into debt traps: The impact may be negative.
  - Example: confrontation in Andhra Pradesh between MFI and Government.

The Impact of Microcredit

- There has been a recent spurt of RCTs that aim to provide evidence on this question
- Special issue in AEJ: Applied in 2015 published six of these studies: India, Ethiopia, Mexico, Mongolia, Bosnia, Morocco. A prior study on philippines appears in *Science*.
- One of two designs
  1. Place-based randomization: MFI selects twice as many villages where they are willing to enter or not enter, and then the researchers randomize where to place program
  2. Randomization "in the bubble" (pioneered by Karlan-Zinman: MFI scores applicants. Highest scores: everyone gets it. Lowest score: no one gets it. In the middle; get it with some probability.
- See Banerjee, Karlan, and Zinman (2015) for a summary
  - Take-up rates are not enormous. RCTs that randomize at the geographical level (e.g. India, Morocco) have first-stages on the order of 10 percentage points or so. Why is this a problem?
  - Impacts on consumption or other welfare measures are close to zero (or if they exist, are small) on average, but there is heterogeneity: imapcts tend to be focused on those who have existing businesses. Why might you expect this?

Meta-analysis: Meager (AEJ 2019)

- There are 7 studies of the same programs in different contexts. How can we say how different or similar they are?
- The issue is that the differences you observe across sites are due to a combination of sampling variation and variation in how the treatment effect actually differ
- Approach:
  - Hierarchical framework: Assume that the treatment effect for site $k \tau_k$ is drawn from a normal distribution $N(\tau, \sigma_k)$.
  - In addition, a sample is drawn on each site, so that the estimated treatment effect is estimated with its own noise:$\widehat{\tau_k}$ is drawn from a normal distribution $N(\widehat{\tau_k}, se_k)$
  - Estimate the model via Bayesian methods (here mainly for tractability). Start with a prior, and use MCMC simulation. Output is a posterior distribution of τ
  - Also measure the extent to which observed variability reflects sampling variation or true heterogeneity in effects (σ): fraction of variation in observed effect that correspond to real variation in the τ_k ("external validity").
  - "Shrinkage": to the extent external validity is high, the average estimated τ is a better estimate of the true treatment effect in a single site than the effect you find in that site.

Results: Posterior distribution of τ

Results: Partial pooling estimates

Results: prior business vs no prior business

So...

- These studies tell us that in general, for the average borrower in the sample, microfinance does not do very much
- Two caveats:
  - Those are marginal clients (new locations or people who barely qualified)
  - Substantial heterogeneity based on whether you had a prior business
- If heterogeneity is important, what else may predict returns? And is there *local* information that can do better than econometricians?

Can the community identify good entrepreneurs?

Hussam, Rigol, and Roth: "Targeting High Ability Entrepreneurs Using Community Information: Mechanism Design in The Field"

- Hussam, Rigol, and Roth's approach:
  - Asked entrepreneurs in peri-urban Maharashtra, India to rank their peers (group of 4-6 people) on metrics of business profitability and growth potential.
  - To assess the validity of their reports, randomly distributed cash grants of USD 100 to a third of these entrepreneurs to measure actual productivity. Why is this important?
  - What's the regression you'd want to run?

$$Y_i = \beta_1 PREDICTED_i + \beta_2 CASHDROP_i + \beta_3 PREDICTED_i \times CASHDROP_i + \epsilon_i$$

  - How to test if this is *better* than machine learning?
  - Step 1: use ML in one sample to predict returns to cash, ML_i, with and without including community ranks
  - Estimate above equation with both predicted outcomes
  - Alternate Step 2:

$$Y_i = \beta_1 PREDICTED_i + \beta_2 CASHDROP_i + \beta_3 PREDICTED_i \times CASHDROP_i + \beta_4 ML_i + \beta_5 CASHDROP_i \times ML_i + \epsilon_i$$

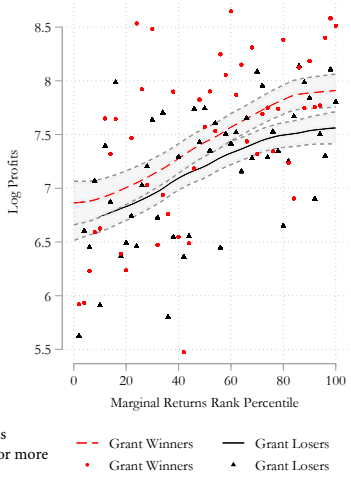
Communities know stuff

Table 1: What Do Respondents Know About One Another?

	(1) Income	(2) Profits	(3) Assets	(4) Medical Exp.	(5) Digitspan	(6) Work Hours
Panel A: Average Rank Level						
Average Rank	1471.23***	1291.41***	103153.36***	1373.28**	0.47***	1.16
	(249.43)	(209.23)	(21711.92)	(517.00)	(0.09)	(1.91)
Panel B: Average Rank Percentile						
Average Rank	0.18***	0.20***	0.22***	0.17***	0.22***	0.02
	(0.03)	(0.03)	(0.03)	(0.06)	(0.04)	(0.07)
Mean of Outcome	8833.84 [6845.50]	6913.14 [6010.60]	475397.89 [719316.80]	2866.78 [5389.32]	5.19 [1.69]	61.32 [22.91]
N	1924	1980	1844	263	281	276
No. HHs	1029	1039	997	263	281	276

Community ranks predict marginal productivity of the grant

Figure 2: Marginal Returns to the Grant by Percentile of the Average Community Ranks Distribution



Community ranks predict marginal productivity of the grant

Table 2: Do Peer Reports Predict True Marginal Returns to the Grant?

	(1) Income	(2) Income	(3) Log Income	(4) Log Income	(5) Profits	(6) Profits	(7) Log Profits	(8) Log Profits
Panel A: Average MR Rank Value								
Winner*Rank	1275.64***	1132.56***	0.22**	0.17*	608.42**	593.15**	0.42**	0.37**
	(459.30)	(339.98)	(0.09)	(0.09)	(290.28)	(235.03)	(0.16)	(0.17)
Winner	-3709.32**		-0.62**		-1352.87		-1.06*	
	(1609.98)		(0.31)		(909.15)		(0.56)	
Panel B: Average MR Rank Tercile								
Winner*Top Tercile Rank	2261.13***	2161.49***	0.34	0.19	1308.19**	1109.81***	0.73**	0.52
	(802.98)	(627.01)	(0.21)	(0.19)	(557.46)	(404.93)	(0.32)	(0.32)
Winner*Middle Tercile Rank	453.22	806.04	0.02	-0.01	117.77	135.78	0.07	-0.06
	(785.55)	(583.89)	(0.18)	(0.18)	(389.00)	(349.62)	(0.29)	(0.31)
Winner	-448.84		0.00		152.12		0.04	
	(622.35)		(0.16)		(374.89)		(0.25)	
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.026**	0.034**	0.062*	0.243	0.027**	0.028**	0.015**	0.032**
Mean of Outcome for Grant Losers	8197.37	8197.37	8.62	8.62	4552.35	4552.35	7.33	7.33
	[6412.25]	[6412.25]	[1.35]	[1.35]	[5159.52]	[5159.52]	[2.55]	[2.55]
Controls		X		X		X		X
N	5324	5324	5342	5342	5319	5319	5337	5337
No. HHs	1336	1336	1336	1336	1336	1336	1336	1336

Mechanisms

Table 3: Impact of Grant on Business Inputs

	(1) Business Inventory	(2) Durable Business Assets	(3) Total Hours Worked Past Week	(4) Total Days Worked Past Month	(5) Total HH Labor	(6) Household Labor Hours Past Week	(7) HH Labor Wage Bill Past Week	(8) Total Non-HH Labor	(9) HH Labor Hours Past Week	(10) Non-HH Labor Wage Bill Past Week
Panel A: Average MR Rank Value										
Winner*Rank	1078.654	11160.866*	5.735***	1.860***	0.008	1.226	10.482	-0.021	1.225	57.689
	(1740.237)	(6575.246)	(1.574)	(0.618)	(0.041)	(1.126)	(6.508)	(0.048)	(2.088)	(71.814)
Winner	-2237.814	-3.75e+04*	-18.606***	-4.827**	-0.039	-5.001	-35.667	0.131	-2.827	-57.556
	(5126.419)	(21246.598)	(5.506)	(2.149)	(0.140)	(3.936)	(34.468)	(0.157)	(7.370)	(268.620)
Panel B: Average MR Rank Tercile										
Winner*Top Tercile Rank	4352.544	17644.134**	9.878***	4.561***	0.059	3.670	19.429*	-0.014	3.132	92.381
	(2681.618)	(8081.621)	(3.006)	(1.293)	(0.084)	(2.522)	(10.647)	(0.082)	(3.264)	(119.214)
Winner*Middle Tercile Rank	1876.845	6616.028	1.756	2.632**	0.043	4.628**	-22.752	-0.223	0.121	-32.290
	(1294.169)	(8746.010)	(3.144)	(1.279)	(0.086)	(2.203)	(35.728)	(0.205)	(3.622)	(166.954)
Winner	-940.295	-9129.990	-3.738	-1.266	-0.050	-3.959*	0.476	0.146**	0.058	112.873
	(1312.308)	(5656.744)	(2.545)	(1.041)	(0.066)	(2.037)	(11.490)	(0.071)	(3.015)	(126.786)
P-value from F-Test										
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.317	0.349	0.007***	0.099*	0.842	0.602	0.292	0.326	0.265	0.374
Mean of Outcome for Grant Losers	6244.33	83645.98	40.63	23.51	0.14	2.88	7.03	0.14	3.83	148.08
	[24614.72]	[1814367.18]	[32.54]	[13.08]	[0.51]	[12.33]	[187.30]	[1.07]	[27.67]	[1273.62]
N	5326	5326	5326	5326	5326	5326	5326	5326	5326	5326
No. HHs	1336	1336	1336	1336	1336	1336	1336	1336	1336	1336

Community has prediction power over and above observables

Table 4: Observable vs. Ranks Prediction

	(1) Income	(2) Income	(3) Log Income	(4) Log Income	(5) Profits	(6) Profits	(7) Log Profits	(8) Log Profits
Winner*Top Tercile Controls	1157.509		0.037		2370.199***		0.014	
	(752.152)		(0.183)		(609.236)		(0.325)	
Winner*Top Middle Controls	1576.349*		0.479		1592.155***		-0.158	
	(868.320)		(0.312)		(499.617)		(0.291)	
Winner*Top Tercile Controls+Rank		3528.869***		0.653***		2745.852***		0.864***
		(728.128)		(0.184)		(570.311)		(0.311)
Winner*Top Middle Controls+Rank		1797.802**		0.320**		1282.037***		0.244
		(793.417)		(0.156)		(424.360)		(0.246)
Winner	-342.438	-1235.090**	0.066	-0.187**	-645.616	-649.324	0.383	-0.028
	(538.084)	(577.000)	(0.173)	(0.090)	(438.570)	(412.903)	(0.250)	(0.210)
P-value from F-Test								
Winner*Top Tercile= Winner*Middle Tercile	0.625	0.033**	0.098*	0.117	0.209	0.007***	0.528	0.031**
Mean of Outcome for Grant Losers	8197.37	8197.37	8.62	8.62	4552.35	4552.35	7.33	7.33
	[6412.25]	[6412.25]	[1.35]	[1.35]	[5159.52]	[5159.52]	[2.55]	[2.55]
N	5324	5324	5342	5342	5319	5319	5337	5337
No. HHs	1336	1336	1336	1336	1336	1336	1336	1336

What makes microfinance *per se* different?

- Default rates in microfinance are extremely low (less than 2%).
- The "canonical" model of microcredit (Grameen Bank) has the following elements: (adopted or not by other MFIs)
  1. Lends almost only to women.
  2. Weekly repayment schedule.
  3. Start repaying immediately.
  4. Group lending (5 to 10 women who know each other), with joint liability.
  5. Regular meetings, where members forge bonds and other things can be discussed (business advice, home advice).
  6. Dynamic incentives (very small loans initially, which become larger over time).
  7. Extensive monitoring by credit officers who are not very well paid and work very hard, with incentives based on number of clients, and repayment rates.
  8. High interest rates (at least 20% a year, often much more).
- Which of these matter?

Lending to women

De Mel, McKenzie, and Woodruff (2008): "Returns to Capital in Microenterprises: Evidence from a Field Experiment"

- Setting:
  - Sri-Lanka after the tsunami
- Experiment:
  - Starting from a census, identified 405 households which had a small business (retail or manufacturing), with less than $1,000 in fixed capital (excluding land and building).
  - Most of the firms have very little in the way of assets (about $100 in machinery or stock).
  - Conducted a survey and offered, as an encouragement to participate in the survey, a random prize drawing:
  - Prize was a small grant ($100 or $200) either in cash or kind of asset, or stock. $100 is equivalent to 3 to 6 months profit. Cash grants were unrestricted.
  - Follow-up survey data was collected on all firms.

Results on Capital

- Very large return to capital: about 60% per year

TABLE II
EFFECT OF TREATMENTS ON OUTCOMES

Impact of treatment amount on:	Capital stock (1)	Log capital stock (2)	Real profits (3)	Log real profits (4)	Owner hours worked (5)
10,000 LKR in-kind	4,793*	0.40***	186	0.10	6.06**
	(2,714)	(0.077)	(387)	(0.089)	(2.86)
20,000 LKR in-kind	13,167***	0.71***	1,022*	0.21*	−0.57
	(3,773)	(0.169)	(592)	(0.115)	(3.41)
10,000 LKR cash	10,781**	0.23**	1,421***	0.15*	4.52*
	(5,139)	(0.103)	(493)	(0.080)	(2.54)
20,000 LKR cash	23,431***	0.53***	775*	0.21*	2.37
	(6,686)	(0.111)	(643)	(0.109)	(3.26)
Number of enterprises	385	385	385	385	385
Number of observations	3,155	3,155	3,248	3,248	3,378

Women

- But no impact for women

TABLE V
TREATMENT EFFECT HETEROGENEITY (DEPENDENT VARIABLE: REAL PROFITS)

					Females	Males
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
Treatment amount	5.41***	7.35**	5.29***	4.96**	2.83	6.74**
	(2.09)	(2.86)	(2.15)	(2.19)	(2.39)	(3.09)
Interaction of treatment amount with:						
Female owner		−7.51*				
		(4.02)				
Number of wage workers			−3.69			
			(2.38)			
Household asset index			−2.43**		−2.88**	−3.05
			(1.14)		(1.35)	(2.06)
Years of education			1.56***		0.24	2.03**
			(0.59)		(0.78)	(0.82)
Digit Span Recall			3.80**		7.34***	1.84
			(1.88)		(2.32)	(2.80)
Risk aversion				0.54		
				(1.25)		
Uncertainty				−7.82		
				(7.31)		
Constant	3,824***	3,777***	3,823***	3,840***	2,860***	4,700
	(174)	(179)	(175)	(174)	(211)	(283)
Firm-period observations	3,248	3,084	3,149	3,218	1,484	1,510
Number of enterprises	385	365	369	381	174	176

Or maybe not?

Bernhardt et al 2019: Household Matters: Revisiting the Returns to Capital among Female Microentrepreneurs

- Bernhardt et al re-examine Del Mel et al (and others).
- Hypothesis: you should be looking at *household* outcomes, not individual outcomes. Why? What do you expect?

TABLE 2—ENTERPRISE PROFITS AND HOUSEHOLD INCOME IN INDIA AND SRI LANKA

	Female enterprise profits (1)	All household enterprise profits (2)	log household monthly income (3)	Differences in treatment effects (col. 2 versus col. 1) (4)
Panel A. India				
β_1: Treatment indicator	167.01	671.58	0.25	491.70
	(103.17)	(218.27)	(0.09)	(231.14)
Control mean	401.08	1,387.35	9.24	
	[949.75]	[1,740.73]	[0.92]	
Number of enterprises	473	473	463	
Panel B. Sri Lanka				
θ_1: Treatment amount	−0.16		0.08	
	(2.82)		(0.04)	
Control mean	37.17		9.13	
	[38.75]		[0.65]	
Number of enterprises	182		182	
Enterprise-period observations	1,529		1,422	

Weekly repayment schedule

Field and Pande (2008): "Repayment Frequency and Default in Micro-finance: Evidence from India"

- Many MFIs are convinced that a regular repayment schedule starting immediately is essential for repayment: it provides discipline, and it is easier for clients to save a small amount towards weekly repayment, rather than large amounts.
- In contrast, many potential clients say they are discouraged from weekly repayment by both the schedule (not appropriate to all activities, e.g., cow rearing), and meetings (time consuming).
- Field and Pande set up a study to test this with an MFI in Kolkata (West Bengal, India).
- After joining the organization, 100 groups were randomized by public lottery into:
  - Regular (weekly) repayment schedule.
  - Monthly repayment schedule with monthly meetings.
  - Monthly repayment schedule with weekly meetings.
- On time repayment was as high in monthly and weekly.

Results

Table 1: Repayment Schedule and Loan Default

	Full loan repaid					
	within 60 weeks		within fifty six weeks		within fifty four weeks	
	(1)	(2)	(3)	(4)	(5)	(6)
Weekly payment	-0.012	-0.016	-0.009	-0.013	0.011	0.010
	(0.022)	(0.022)	(0.022)	(0.023)	(0.028)	(0.029)
Monthly payment, weekly meeting	-0.005	-0.005	-0.012	-0.012	-0.042	-0.038
	(0.014)	(0.014)	(0.017)	(0.017)	(0.040)	(0.040)
Control variables	No	Yes	No	Yes	No	Yes
Observations	1017	1005	1018	1006	1028	1016
Mean value, monthly payment, monthly meeting	0.987 (0.112)		0.985 (0.122)		0.964 (0.185)	

Impact on Social Capital

Feigenberg, Field, and Pande (2013): "The Economic Returns to Social Interaction: Experimental Evidence from Microfinance"

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	3.005***	2.045**	0.069*	0.070*	0.186**
(Weekly–Weekly)	(0.107)	(1.001)	(0.038)	(0.039)	(0.080)
Panel B: Controls included					
Treatment 1	3.052***	2.054**	0.081**	0.071**	0.199***
(Weekly–Weekly)	(0.092)	(0.891)	(0.039)	(0.035)	(0.073)
Control mean		5.475	0.153	0.229	
(Monthly–Monthly)		[10.386]	[0.360]	[0.421]	
Specification	OLS	OLS	Probit	Probit	OLS
N	684	3026	3023	3026	3026

Impacts

TABLE 4
Meeting frequency and default: evidence from the second loan cycle

	Default		Group met weekly	Default
	(1)	(2)	(3)	(4)
Panel A: No controls				
Treatment 1	−0.052**	−0.052**		
(Weekly–Weekly)	(0.021)	(0.021)		
Treatment 2 (Weekly–Monthly)*			−0.118***	
heavy rain days			(0.020)	
Treatment 2			1.086***	
(Weekly–Monthly)			(0.152)	
Heavy rain days			0.025	
			(0.016)	
Group met weekly				−0.077**
				(0.038)
Panel B: Controls included				
Treatment 1	−0.036**	−0.045**		
(Weekly–Weekly)	(0.016)	(0.021)		
Treatment 2 (Weekly–Monthly)*			−0.124***	
heavy rain days			(0.020)	
Treatment 2			1.086***	
(Weekly–Monthly)			(0.147)	
Heavy rain days			0.024	
			(0.018)	
Group met weekly				−0.092**
				(0.042)
F Statistic			*20.16*	
p-value			*[0.000]*	
Control mean (Monthly–Monthly)	0.072			
	[0.258]			
Specification	Probit	OLS	OLS	Linear IV
N	698	698	720	720

Start repaying immediately

Field, Pande, Papp, and Rigol (2013): "Does the Classic Microfinance Model Discourage Entrepreneurship Among the Poor? Experimental Evidence from India"

- A very odd feature of microfinance is that you need to start repaying the loan as soon as you get it – i.e. the next week.
- Why might they do this? Why is this odd?
- Experiment:
  - Some get normal contract with repayment starting immediately
  - Some get two-month grace period before they have to repay
- What might you expect?

Changes loan use

TABLE 1—IMPACT OF GRACE PERIOD ON LOAN USE AND BUSINESS FORMATION

		Coefficient on grace period dummy (SE)	
	Control group mean (SD) (1)	OLS (no controls) (2)	OLS (with controls) (3)
Panel A. Total business spending	6,142.4	364.9**	383.9**
	(162.4)	(180.1)	(185.2)
Component-wise business spending			
Inventory and raw materials	4,521.4	337.1	367.6
	(226.3)	(279.9)	(272.8)
Business equipment	1,536.5	8.786	−14.4
	(172.4)	(234.1)	(227.1)
Operating costs	84.46	19.01	30.75
	(36.91)	(48.37)	(49.38)
Panel B. Total nonbusiness spending	1,149.1	−356.1**	−371.6**
	(149.1)	(172.4)	(178.7)
Component-wise nonbusiness spending			
Home repairs	557.2	−208.8**	−222.1**
	(116)	(105.1)	(110.4)
Utilites, taxes, and rent	25.95	−8.214	−9.657
	(15.66)	(19.9)	(20.66)
Human capital	237.9	−34.97	−33.06
	(76.88)	(90.26)	(91.99)
Money for relending	197.6	−27.42	−30.13
	(56.74)	(70.61)	(69.51)
Savings	131.6	−15.02	−10.75
	(35.97)	(47.12)	(47.48)
Food and durable consumption	151	−91.79	−94.73
	(76.21)	(94.11)	(97.86)
Panel C. New business	0.02	0.0268**	0.0258*
	(0.00648)	(0.0135)	(0.0139)

Increases default rates

TABLE 3—IMPACT OF GRACE PERIOD ON DEFAULT

	Full loan not repaid				Repayment history		
	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)	Made first half of loan repayments on time (6)	Made first payment (7)
Panel A. (*No controls*)							
Grace period	0.0901**	0.0696**	0.0614**	148.7*	−0.0137	−0.00842	0.0288
	(0.0349)	(0.0280)	(0.0251)	(83.61)	(0.0151)	(0.0613)	(0.0261)
Panel B. (*With controls*)							
Grace period	0.0845**	0.0642**	0.0609**	149.0*	−0.0156	−0.0246	0.0244
	(0.0333)	(0.0262)	(0.0249)	(83.55)	(0.0159)	(0.0534)	(0.0240)
Observations	845	845	845	845	845	845	845
Control mean	0.0424	0.0212	0.0165	69.65	0.988	0.501	0.953
	(0.0142)	(0.0101)	(0.00899)	(40.15)	(0.00774)	(0.0427)	(0.0231)

But increases 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)
Panel B. Top coded sample						
Grace period	645.0***	640.9***	0.195**	0.202**	23,594.1***	29,068.9***
	(214.6)	(208.1)	(0.0801)	(0.0778)	(8,849.6)	(9,432.4)
Observations	752	752	749	749	766	766
Control mean	1,579.3	1,579.3	18,110.65	18,110.65	35,535.9	35,535.9
	(117.9)	(117.9)	(26,962.41)	(26,962.41)	(4,951.8)	(4,951.8)
Panel C. Top coded sample and trimmed at 1 percent						
Grace period	503.8***	486.5***	0.190**	0.199**	15,266.2**	19,010.0***
	(182.8)	(176.8)	(0.0798)	(0.0770)	(6,825.5)	(7,067.9)
Observations	748	748	744	744	761	761
Control mean	1,514.7	1,514.7	17,160.57	17,160.57	33,030.8	33,030.8
	(102.7)	(102.7)	(23,571.94)	(23,571.94)	(4,238.4)	(4,238.4)
Panel D. Top coded sample and trimmed at 5 percent						
Grace period	440.5**	452.6**	0.198**	0.207***	15,266.2**	19,010.0***
	(175.9)	(175.3)	(0.0795)	(0.0768)	(6,825.5)	(7,067.9)
Observations	747	747	743	743	761	761
Control mean	1,514.7	1,514.7	16,692.76	16,692.76	33,030.8	33,030.8
	(102.7)	(102.7)	(21,739.62)	(21,739.62)	(4,238.4)	(4,238.4)

And business size

TABLE 4—IMPACT OF GRACE PERIOD ON BUSINESS SIZE AND BUSINESS BEHAVIOR

	Business closure (1)	Average difference in profits between high- and low-profit months (2)	Sold goods or services at a discount to make loan payment (3)	Customers buy on credit (4)	Customers pre-order goods or service (5)	Number of goods and services provided (6)
Panel A. (*No controls*)						
Grace period	−0.0718**	686.6*	−0.0232*	0.0972**	0.0989***	5.543**
	(0.0324)	(375.7)	(0.0128)	(0.0373)	(0.0356)	(2.467)
Panel B. (*With controls*)						
Grace period	−0.0669**	713.9*	−0.0166	0.113***	0.107***	6.051**
	(0.0334)	(396.6)	(0.0122)	(0.0371)	(0.0358)	(2.566)
Observations	766	751	764	769	769	769
Control mean	0.386	2,361.6	0.0468	0.432	0.395	5.607
	(0.0243)	(242.0)	(0.0112)	(0.0270)	(0.0236)	(0.475)

Group Lending

- This is probably the feature of microcredit which has attracted the most attention: People are responsible for each other's loan (they cannot borrow again if the group does not reimburse).
- Two potential beneficial effects:
  - A screening effect: People will only want to join other reliable people (Ghatak).
  - A monitoring effect: People will monitor each other (for free).
- Yet, it has drawbacks: it may create excessive pressure, and discourage some clients from borrowing since you have to pay for the default of others.
- Many microfinance organizations are quietly moving away from it. Even Grameen Bank does not practice joint liability any more, but "group lending with individual liability": the group.

Testing group lending

Gine and Karlan (2014): "Group versus Individual Liability: Long Term Evidence from Philippine Microcredit Lending Groups"

- In 2004-2005, *after group formation*, Green Bank of Caraga converted 56 centers (randomly selected out of 106) from joint liability to individual liability. Weekly group meetings still held, but now people are not jointly responsible: pure moral hazard effect.
- Three years later: Percent in default (or delay in repayment) is exactly the same in both type of center. But smaller loans. And more loan growth.
- Green Bank then randomly selected different areas to implement *from the start* (adverse selection and moral hazard effects):
  - Group liability;
  - Individual liability (still grouped based); and
  - Staggered: First loan cycle is group, and then individual onwards, if repayment was high.
- Also no impact

Results

Table 2A
Institutional impact at the loan cycle level, conversion areas.

Explanatory variable	(1) Proportion of missed weeks	(2) Indicator for having at least one missed week	(3) Proportion of past due balance, at maturity date	(4) Indicator for having past due, at maturity date	(5) Proportion of past due balance, 30 days after maturity date	(6) Indicator for having past due, 30 days after maturity date	(7) Total excess savings	(8) Loan size
Panel A: Baseline clients								
All loans								
Individual liability	0.005	−0.004	−0.001	0.008	−0.000	0.011	−309.973**	−924.722***
	(0.014)	(0.034)	(0.001)	(0.012)	(0.001)	(0.011)	(131.414)	(317.470)
Observations	14,333	14,333	14,333	14,333	14,182	14,182	14,333	14,333
R-squared	0.102	0.099	0.036	0.227	0.024	0.243	0.303	0.166
Mean of dependent variable	0.075	0.430	0.002	0.045	0.001	0.031	842.3	6844.4
'Hump' loans only: disbursed before and matured after the conversion date								
Individual liability	0.003	0.012	−0.001	0.006	−0.000	−0.000	−51.803*	−540.902
	(0.015)	(0.052)	(0.001)	(0.009)	(0.000)	(0.000)	(28.772)	(359.792)
Observations	2985	2985	2985	2985	2985	2985	2985	2985
R-squared	0.158	0.130	0.010	0.033	0.006	0.006	0.061	0.202
Mean of dependent variable	0.073	0.445	0.001	0.010	0.000	0.000	248.3	7947.0
Panel B: New clients								
Individual liability	0.005	0.006	−0.002	0.013	−0.000	0.025	−239.652	−817.838***
	(0.006)	(0.025)	(0.001)	(0.019)	(0.001)	(0.018)	(170.740)	(195.273)
Observations	6049	6049	6049	6049	5662	5662	6046	6049
R-squared	0.096	0.110	0.016	0.093	0.014	0.114	0.063	0.068
Mean of dependent variable	0.069	0.385	0.008	0.168	0.003	0.129	1895.4	5284.3

Results

Table 2B
Institutional impact at the loan cycle level, new areas.

	(1) Proportion of missed weeks	(2) Indicator for having at least one missed week	(3) Proportion of past due balance, at maturity date	(4) Indicator for having past due, at maturity date	(5) Proportion of past due balance, 30 days after maturity date	(6) Indicator for having past due, 30 days after maturity date	(7) Loan size
Panel A: All cycles							
Individual liability	−0.004	0.002	−0.005	−0.018	−0.002	−0.018	−139.556***
	(0.016)	(0.054)	(0.006)	(0.026)	(0.004)	(0.014)	(177.596)
Phased-in individual liability	−0.001	0.067	−0.004	−0.010	−0.004	−0.015	−237.521
	(0.016)	(0.054)	(0.006)	(0.026)	(0.004)	(0.013)	(179.535)
Number of observations	4869	4869	4869	4869	4704	4704	5356
R squared	0.151	0.227	0.115	0.138	0.123	0.187	0.138
Mean of dependent variable	0.098	0.493	0.023	0.122	0.014	0.068	4390.067

Social capital

Karlan (2007): "Social Connections and Group Banking"

- The group structure could still be important for microcredit, as a support and reputation structure.
- "Social Capital" (Robert Putnam): web of interactions which exist between people and help them achieve better outcomes through mutual cooperation.
- Natural experiment: in Ayacucho, Peru, FINCA assigns individuals to groups quasi-randomly, in the order in which they visit the office to join.
- Group members may live close or far; may be from same or different culture.
- Results, focusing on people who came uninvited:
  - Default is lower when more members live close by.
  - Default is lower when more members have the same culture.

Table 4

Individual Default

OLS, Tobit, and Probit

	Dependent variable: % of loan in default at end of cycle					
	1st Loan Only			All Loans		
	OLS (1)	Tobit (2)	Probit (3)	OLS (4)	Tobit (5)	Probit (6)
Distance from individual's home to original members of group	0.019 (0.077) $n = 616$	0.343 (0.342) $n = 616$	0.019 (0.019) $n = 616$	0.049 (0.068) $n = 1{,}801$	0.297 (0.024) $n = 1{,}801$	0.040 (0.027) $n = 1{,}801$
% of original members within 10-minute walk of individual's home	−1.536*** (0.391) $n = 616$	−6.077*** (1.795) $n = 616$	−0.284*** (0.079) $n = 616$	−1.556*** (0.370) $n = 1{,}801$	−3.754*** (1.078) $n = 1{,}801$	−0.367*** (0.134) $n = 1{,}801$
% of original members with same culture as individual	−0.534* (0.301) $n = 616$	−4.230** (1.791) $n = 616$	−0.200*** (0.069) $n = 616$	−0.396 (0.308) $n = 1{,}801$	−1.458 (1.116) $n = 1{,}801$	−0.177 (0.111) $n = 1{,}801$

Other topics in credit

- Indigenous institutions
  - ROSCAs
- Demand for credit
  - Kaboski and Townsend estimate a structural model of demand for credit in the context of a microcredit expansion (in recitation)
  - Provide a story similar to that in the Banerjee et al paper: looks like there is heterogeneity in impacts depending on where you are with respect to opening a business.
  - Credit can also increase consumption since you no longer need large buffer stocks
- Macro impacts
  - Several papers show that credit constraints lead to large inequality in marginal return to capital
  - Understanding banks as intermediaries
  - Much more in 14.772

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