Development Economics

Mobile Money and Credit

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AEA Continuing Education

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Roadmap

1. Mobile Money
2. Credit: Why is Lending So Hard?
3. Returns to Credit Expansions
4. Equilibrium Effects of Credit Access
5. Improving Credit Product Design
6. Digital Finance

Mobile Money

M-Pesa in Kenya is most famous example:

- Mobile wallet linked to SIM card
- Cash in/out at network of agents
- Low cost P2P transfers
- Can save in wallet
- Fees for cash out / transfers, much lower than pre-existing banks

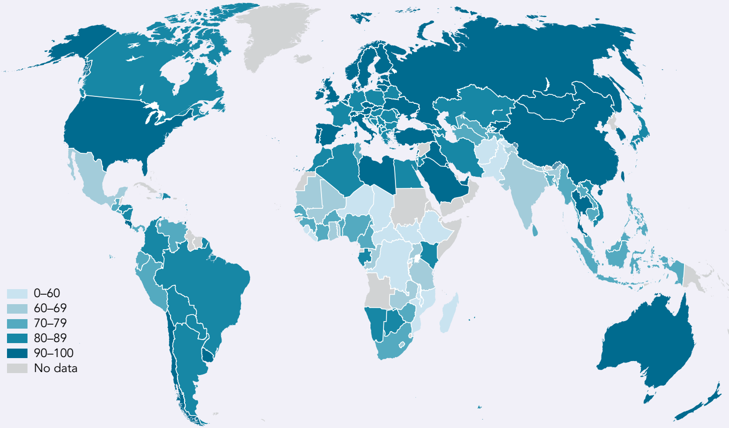
Large increase in global digitization of payments during COVID

Why Mobile Money?

MAP S.1

Mobile phone ownership around the world

Adults with a mobile phone (%), 2017



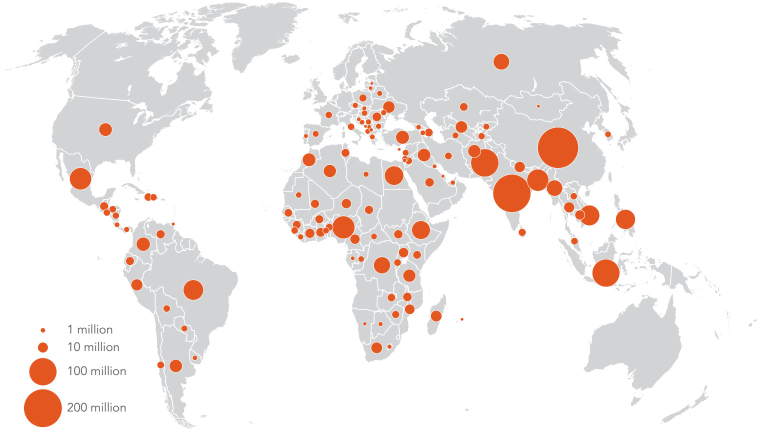
Source: Gallup World Poll 2017.

Why Mobile Money?

MAP 2.1

Globally, 1.7 billion adults lack an account

Adults without an account, 2017



Source: Global Findex database.

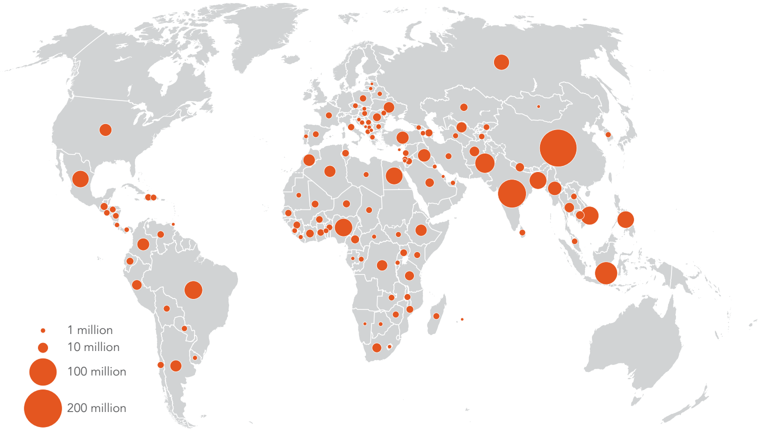
Note: Data are not displayed for economies where the share of adults without an account is 5 percent or less.

Why Mobile Money?

MAP 6.1

Two-thirds of unbanked adults have a mobile phone

Adults without an account owning a mobile phone, 2017



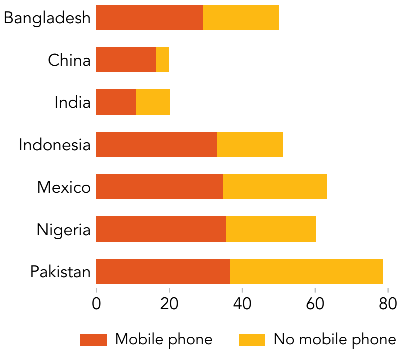
Sources: Global Findex database; Gallup World Poll 2017.
Note: Data are not displayed for economies where the share of adults without an account is 5 percent or less.

Why Mobile Money?

FIGURE 6.1

Mobile phone ownership among the unbanked varies across economies but tends to be high

Adults without an account (%), 2017



Sources: Global Findex database; Gallup World Poll 2017.

Mobile Money and Risk Sharing

Some of the best evidence uses mobile money:

- Mobile money's primary use is for making payments between people!
- What unit of risk sharing are we likely to pick up with mobile money data?
- Josh Blumenstock has some very interesting work using mobile money administrative data
  - But, hard to get access to the full universe of transactions
  - ENORMOUS data sets – requires specialized CS tools
  - See, for example: `https://vimeo.com/27316698`(video of airtime transfers in Rwanda following an earthquake that occurred at 9:30am)

Jack and Suri (2014)

"Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution" AER (2014)

State of the art empirical work for insurance lit

- Research question: what is the effect of increased access to mobile money on households' consumption risk?
- Authors conducted household panel from 2008-2010
- First, diff-in-diff: include household fixed effects to compare changes in the response of consumption to shocks across M-PESA users and nonusers.
- Second, diff-in-diff: use expansion of agent network during panel to proxy for access to M-PESA

Jack and Suri (2014): Timing

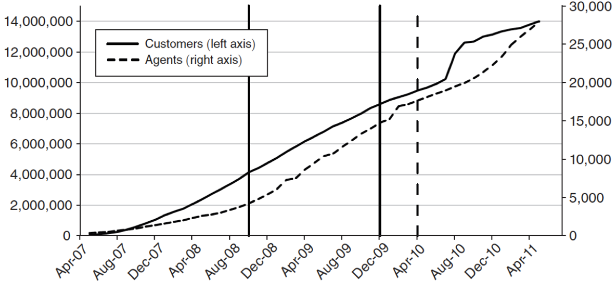


FIGURE 1. M-PESA CUSTOMER REGISTRATIONS AND AGENTS

Notes: The solid vertical lines indicate when the household survey rounds were conducted. The dashed vertical line represents when the agent survey was administered.

- Fortunate timing of survey rounds and rise of M-Pesa

Jack and Suri (2014): Transfer types

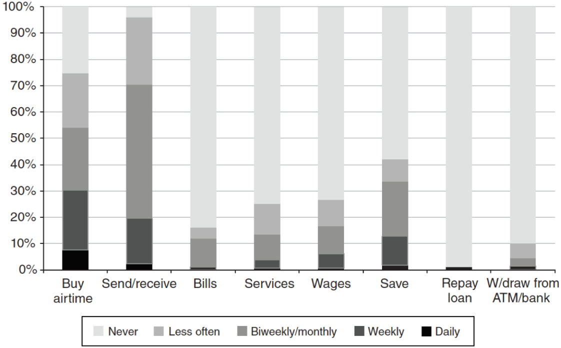


FIGURE 2. FREQUENCY OF MPESA USE, BY TRANSACTION TYPE

Notes: Figures are based on the 2010 survey covering about 1,000 individual users, which collected data on 31 separate transactions that M-PESA allows. These figures aggregate most of those transactions but do not include balance and pin number checks.

- Is it clear that M-PESA only improves risk mitigation through informal risk-sharing? What else could be happening?
- What do we need to see to conclude that risk-sharing is happening?

Jack and Suri (2014)

Defining shocks:

- Diff-in-diff specification requires that shocks be exogenous and uncorrelated with "treatment" assignment (here, access to M-PESA)
- HHs reported any unexpected events in past six months, pos and neg. expected events.

Hypotheses:

1. The consumption of M-PESA users should respond less to shocks than that of non-users
2. To the extent that these differences arise from differences in remittance behavior, remittances should respond more to shocks for M-PESA users than for nonusers;
3. The network of active participants in risk-sharing should be larger for users than nonusers.

Jack and Suri (2014): Results

TABLE 4A—BASIC DIFFERENCE-IN-DIFFERENCES RESULTS

	Total consumption Full sample				
	OLS (1)	Panel (2)	Panel (3)	Panel (4)	Panel (5)
M-PESA user	0.5730***	0.0520	0.0456	−0.0223	−0.0088
	[0.0377]	[0.0481]	[0.0469]	[0.0484]	[0.0449]
Negative shock	−0.2111***	−0.0668	−0.0727	0.2872	0.2673
	[0.0381]	[0.0491]	[0.0468]	[0.1762]	[0.1799]
User × negative shock	0.0917*	0.1093*	0.1320**	0.1749***	0.1483**
	[0.0506]	[0.0616]	[0.0594]	[0.0663]	[0.0599]
Demographic controls			Yes	Yes	Yes
Controls + interactions				Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Time × location FE		Yes	Yes		Yes
Observations	4,562	4,562	4,562	4,545	4,545
Negative shock	−0.1593***	−0.0050	0.0019	0.0022	−0.0059
	[0.0252]	[0.0305]	[0.0292]	[0.0286]	[0.0280]
Shock, users	−0.1194***	0.0425	0.0592	0.0518	0.0460
	[0.0335]	[0.0379]	[0.0370]	[0.0383]	[0.0355]
Shock, nonusers	−0.2111***	−0.0668	−0.0727	−0.0626	−0.0737*
	[0.0381]	[0.0491]	[0.0468]	[0.0447]	[0.0429]
Shock, nonusers$\|_{\text{user } Xs}$				−0.1230**	−0.1024**
				[0.0549]	[0.0502]
Mean of user	0.5656	0.5656	0.5656	0.5661	0.5661

Notes: Dependent variable: log total household consumption per capita. Heteroskedasticity-robust standard errors in

Similar results with variation from agent expansion

Jack and Suri (2014): Results

TABLE 5A—MECHANISMS (*Panel*)

	Overall shock: sample w/out Nairobi				Overall shock: w/out Mombasa		Illness shock	
	Pr [receive]		Number received	Total received (square root)	Pr [receive]	Total received (square root)	Pr [receive]	Total received (square root)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M-PESA user	0.1897***	0.1528***	0.2574**	10.6757***	0.1143**	9.0579**	0.1726***	12.5548***
	[0.0456]	[0.0487]	[0.1305]	[3.7863]	[0.0517]	[4.0683]	[0.0420]	[3.1596]
Negative shock	−0.0442	−0.0409	−0.1306	1.8775	−0.1027	−1.8885	−0.1417	−9.3597
	[0.0390]	[0.1438]	[0.4193]	[12.0864]	[0.1452]	[12.4371]	[0.1457]	[10.9683]
User × shock	0.0923*	0.1337**	0.3286*	8.3428*	0.1733***	10.0472**	0.1598**	8.6003
	[0.0530]	[0.0633]	[0.1789]	[4.6884]	[0.0666]	[4.9200]	[0.0722]	[5.2788]
Controls + interactions		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,928	3,911	3,911	3,873	3,703	3,665	3,911	3,873
R^2	0.199	0.218	0.184	0.203	0.223	0.205	0.223	0.209
Shock effect	0.0066	0.0099	−0.0369	1.6647	0.0043	1.5026	0.0161	2.7412
	[0.0282]	[0.0288]	[0.0871]	[2.2697]	[0.0297]	[2.3569]	[0.0315]	[2.5233]
Shock, users	0.0481	0.0478	0.0470	4.3755	0.0543	4.6901	0.0735*	6.5410*
	[0.0383]	[0.0381]	[0.1157]	[3.4195]	[0.0391]	[3.5678]	[0.0433]	[3.5215]
Shock, nonusers	−0.0442	−0.0366	−0.1400	−1.6403	−0.0561	−2.3154	−0.0544	−1.8914
	[0.0390]	[0.0407]	[0.1221]	[2.6656]	[0.0425]	[2.7528]	[0.0442]	[3.0544]
Mean of user	0.5504	0.5512	0.5512	0.5494	0.5470	0.5450	0.5512	0.5494

Mobile Money and Risk Sharing: Thoughts?

- How does this speak to the earlier risk sharing literature (using the ICRISAT villages)?
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- Does this tell us anything about hidden income or limited commitment?
  - Baseler (2023) - migrants have incentives to under-report incomes, might limit migration.
  - However, in Jack and Suri (2014), transfers do flow, so hard to know how much hidden income binds in response to shocks

Digital Payments and Social Protection

In addition to P2P payments, G2P transfers common:

- Aker et al (2016)
  - RCT disbursing disaster relief in Niger through MM vs. Cash ($45 over 5 mos.)
  - MM reduced distance to cash out, improved food security of beneficiaries
- Muralidharan et al (2016)
  - Context: India's national rural work guarantee scheme (MGNREGS)
    - Right to 100 days of publics works labor per year
    - Problem: payment delays, ghost beneficiaries, leakages
  - RCT: Biometric-linked smartcards for worker payments, cash out with agents
    - Randomization "at scale", 19 million people in roll-out in Andhra Pradesh state.
  - Results: Workers paid more quickly, leakage ↓, program participation ↑

Economic Impacts of Covid

Large drops in income across the world among poor households early in Covid pandemic:

- Kenya: 59% $\downarrow$ labor earnings, 71% $\downarrow$ bus. profits (Nov. 2019 to Jun. 2020)
- Zambia: 64% HHs report inability to buy food b/c of $\downarrow$ in income, 35% $\downarrow$ in meals (July 2020)
- Colombia: 57% of those with a pre-pandemic job still had work in June

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Potential for large impacts of transfer programs:

- Many countries have social transfer programs
- Many also pushed emergency relief through these systems

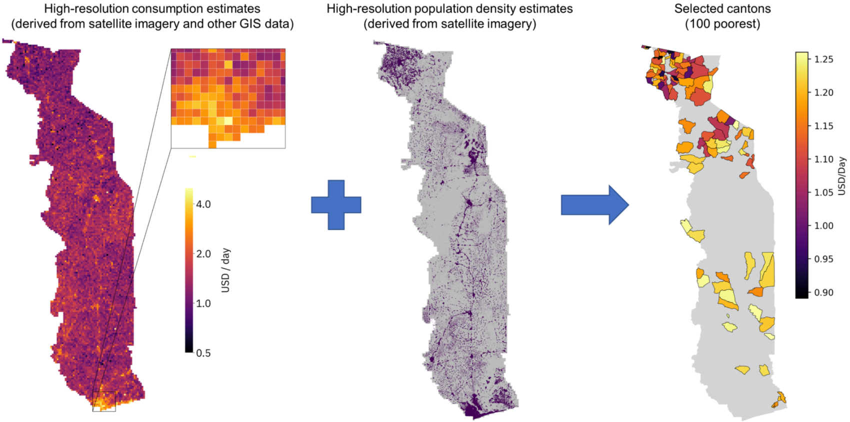
COVID 19 increased digitization, many countries pushed payments through digital systems

- With digital delivery, how to improve targeting of resources?

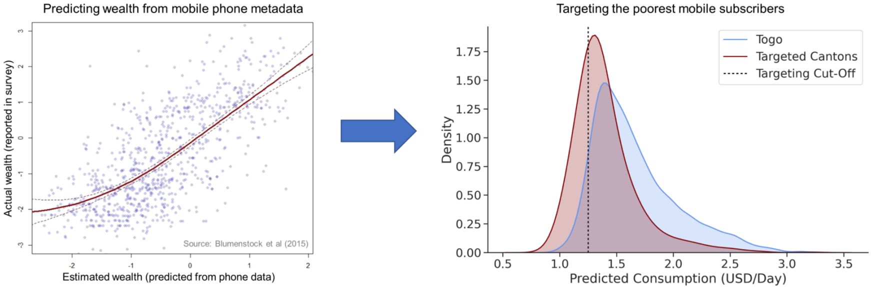
Targeting the Poor in Togo: Steps

Blumenstock et al (2023): Partnership between researchers, GiveDirectly, government of Togo Steps:

1. Identify poorest communities (cantons)
   - Satellite data (can measure roof type, agricultural harvest, population density)
2. Identify poorest households in those target communities
   - Mobile phone data, mobile transfers + ML/AI models
   - Models need "ground truth" – conduct small number of household suveys to measure need that can be matched to the mobile phone data

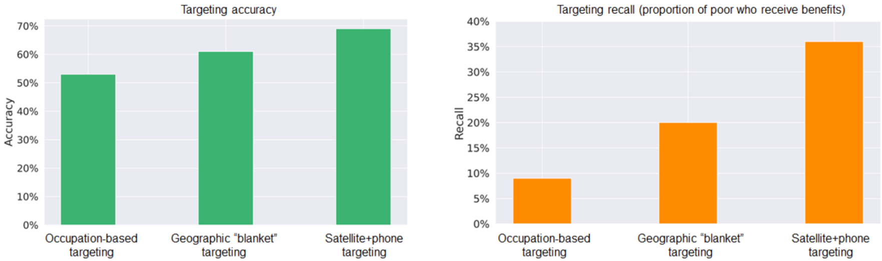


PRIORITIZING THE POOREST VILLAGES AND NEIGHBORHOODS. We produce micro-estimates of the wealth of each 2.4km grid cell by applying deep learning algorithms to high-resolution satellite imagery (left), combine those estimates with information on the population density of each grid cell (middle), and use this information to determine the 100 poorest cantons in Togo (right).



PRIORITIZING THE POOREST INDIVIDUALS/SUBSCRIBERS. Using ground truth wealth and poverty collected through a large phone survey of active mobile phone subscribers, we train machine learning algorithms to estimate the wealth of each mobile subscriber (left). In the 100 poorest cantons (red distribution in right figure), those estimated to consume less than $1.25/day are prioritized for Novissi (dashed vertical line). These individuals are substantially poorer than the average resident of Togo (blue distribution).

Performance vs. Govt Alternatives



COMPARISON OF THE PHONE+SATELLITE APPROACH TO FEASIBLE ALTERNATIVES: In simulations, we assume each of the three possible approaches to targeting benefits has a budget constraint of paying no more than 57,000 beneficiaries. Figure shows the accuracy of each mechanism at reaching the poorest (i.e., the lowest consumption individuals in the 100 poorest cantons), simulated using a phone survey of 9,484 individuals living in those cantons, conducted in September 2020.

Roadmap

Credit vs. Savings

In models with complete markets and no frictions, we typically think of households as being either savers or borrowers, not both.

- Consumption smoothing
  - Borrow when u'(c) high, save when u'(c) low
  - I either want to save or borrow each period, never both
- Profitable investments
  - If I have really great investment opportunities in my business, I want to borrow to invest in my business, not save. Don't want to delay!
  - If I don't have great investment opportunities in my business, I may prefer to save in the bank rather than invest in my business.

What should we expect credit to do?

However, underserved populations don't live in a world with perfect markets

- Internal frictions (e.g., present bias)
- External frictions (limited access, social taxation, social norms)

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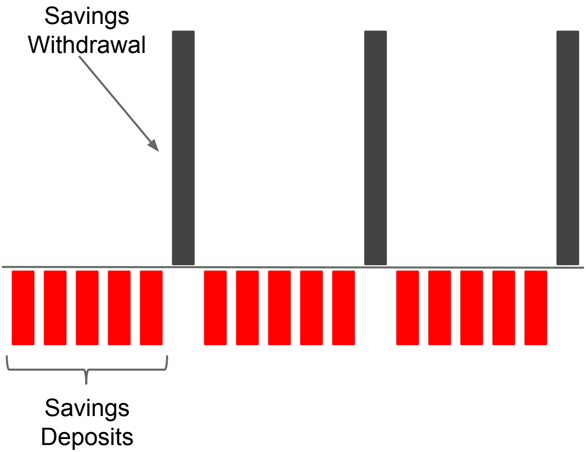
Role for credit in each:

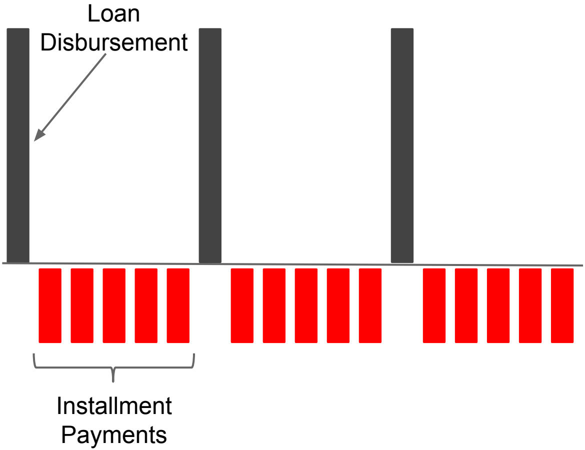
- In PIH model, optimal strategy uses savings and borrowing
  - Savings buffers can be a partial substitute for credit – play a similar role, especially given savings constraints
- For productive investments, access to credit can allow entrepreneur to reach the optimal scale right away – no need to wait while savings accumulates

Savings Cycles



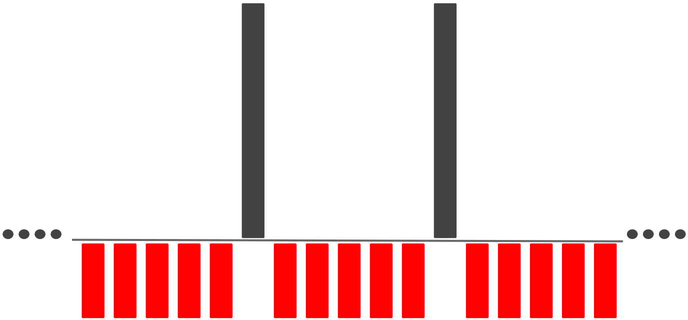
- Possible to accumulate resources through savings cycles

Credit Cycles



- Credit cycles change the timing of the large payouts

Credit Looks Like Savings



- Once cycle starts, savings and credit look the same.

Credit Looks Like Savings

Many financial products observed in developing countries combine savings and credit (recall last lecture)

- Rotating Savings and Credit Associations (RoSCAs)
- Self Help Groups (SHGs)
- Village Savings and Loan Associations (VSLAs)

Or, generate credit cycles with the contract structure:

- Microfinance

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Punchline: savings and credit have A LOT in common, practically and theoretically speaking when there are constraints and market imperfections. (Afzal et al 2018)

- Recall Fink et al (2020), credit helps farmers smooth during hungry season, but predictable scarcity also indicative of failure to save.

Roadmap

Information Frictions and Lending

Classic information asymmetries plague credit markets:

- Adverse selection (Hidden type)
- Moral hazard (Hidden action)
  - Effort under-provision
  - Strategic default (i.e., fail to pay even when resources are available)

Typical solutions:

- Screening
  - Due diligence: visit business, talk to manager
  - Review accounting statements, growth projections...
  - Query the credit registry (often government-run)
- Monitoring
  - Pay costs to monitor effort
- Enforcement
  - Use courts to enforce creditor claims (e.g., collateral)
  - Income garnishment

Problem: all these solutions traditionally harder for formal banking sector in developing country contexts.

Measuring Adverse Selection and Moral Hazard

Karlan and Zinman (2008) AER

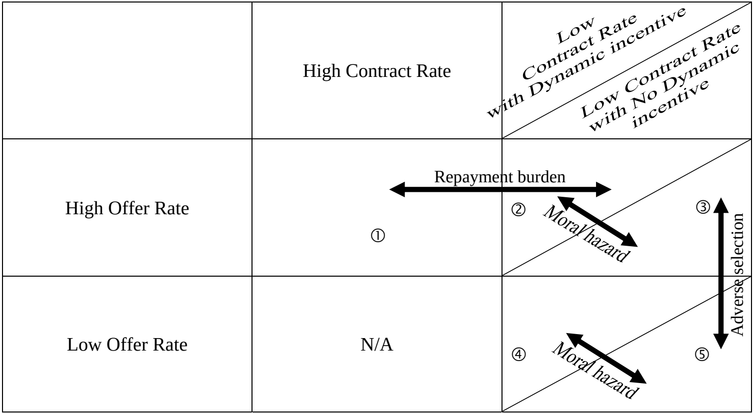
- Question: what is the elasticity of credit demand wrt interest rate?
- They find that those who receive a higher offer are (somewhat) less likely to borrow.
- Higher interest rate $\implies \downarrow$ repayment (10.5% vs. 8.2%)

Problem

- $\uparrow$ Default could be due to AS or MH (repayment burden)
  - Those who agree to borrow at high rates could have higher income risk (worse outside options)
  - Higher interest rate $\implies \downarrow$ effort
  - Wealth or income effects (cannot afford to pay).

Classic paper "Observing Unobservables" by Karlan and Zinman (2009) proposes experimental test to decompose effects

KZ (2009): Experimental Design



- Separate offer rate from contract rate (surprise some people with lower rate at disbursement)
- Randomize dynamic incentive (lower future rate upon repayment), pure MH

KZ (2009): Results

Table 3. Identifying Adverse Selection, Repayment Burden, and Moral Hazard: Comparison of Means

	Selection Effects			Repayment Burden Effects			Moral Hazard Effects		
	High Offer, Low Contract	Low Offer, Low Contract	t-stat: diff≠0	High Offer, High Contract	High Offer, Low Contract	t-stat: diff≠0	No Dynamic Incentive, Low Contract	Dynamic Incentive, Low Contract	t-stat: diff≠0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average Monthly Proportion Past Due	0.102	0.082	1.90*	0.105	0.102	0.23	0.094	0.079	1.94**
	(0.009)	(0.004)		(0.006)	(0.009)		(0.006)	(0.005)	
Proportion of Months in Arrears	0.211	0.202	0.72	0.244	0.211	2.38**	0.217	0.188	2.70***
	(0.011)	(0.006)		(0.008)	(0.011)		(0.008)	(0.008)	
Account in Collection Status	0.123	0.101	1.50	0.139	0.123	0.99	0.118	0.092	2.16**
	(0.013)	(0.007)		(0.009)	(0.013)		(0.008)	(0.008)	
# of observations	625	2087		1636	625		1458	1254	

- Strongest evidence of moral hazard (dynamic incentives)
- Limited adverse selection: but sample drawn from former clients with good repayment, interest rates all lower than market. Not conducive to much AS

How prevalent is strategic default?

Actually a very difficult question to answer:

- Often impossible to disentangle from distressed default in practice

Blouin and Macchiavello (2019, QJE) have a clever way to measure strategic default:

- Setting: coffee mills in 24 countries selling to the international market and borrowing from one specific lender (shared data)

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Blouin and Macchiavello (2019, QJE) have a clever way to measure strategic default:

- Setting: coffee mills in 24 countries selling to the international market and borrowing from one specific lender (shared data)
- Two types of contracts, signed in advance
  - Fixed price (determined at time of signing)
  - Differential price (tracks global coffee spot prices, price determined at delivery)
  - Contract types trade off incentives and price insurance
- Empirical test:
  - Look at prevalence of default when world coffee prices increase between the contract and delivery date for fixed price contracts
  - Can use differential contracts as a placebo

Detecting strategic default

Table II: Strategic Default I: Unexpected price increases and defaults on loans

Dependent Variable:	Default (Baseline Definition)							
Data:	Contract Level						Loan Level	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price Surprise	0.304**	0.343**	0.305**	0.279**	0.369**	0.0360	-0.0661	-0.0253
	(0.121)	(0.154)	(0.139)	(0.122)	(0.171)	(0.0679)	(0.0767)	(0.0875)
Fixed							-0.253**	-0.288**
							(0.111)	(0.125)
Fixed x Price Surprise							0.196**	0.201*
							(0.0907)	(0.103)
Sample	Fixed	Fixed	Fixed	Fixed	Fixed	Differential	All	All

- Fixed: default $\uparrow$ when actual prices higher than contract
- Problem: doesn't rule out distressed default if profits are lower when prices are higher (e.g., mill's costs)

Detecting strategic default

Restrict to price increases out of season (no impact to mill's costs):

Table III: Strategic Default II: Unexpected out of season price increases and defaults

Dependent Variable:	**Default or 90+ days late on repayment**				
	Fixed Price			**Differential Price**	**Fixed Price**
In / Out of Harvest Season	**Out**				**In**
Event Window:	**2-weeks**	**1-week**	**3-weeks**	**2-weeks**	
	(1)	(2)	(3)	(4)	(5)
Shipment Scheduled After Price Jump	0.143***	0.118***	0.105***	-0.00479	0.0438
	(0.0132)	(0.00352)	(0.0387)	(0.0584)	(0.0856)
Control Group Mean of Dependent Variable	0.055	0.005	0.074	0.065	0.091
N	123	70	154	150	72
R^2	0.026	0.044	0.015	0.000	0.002

Notes: The Table reports results for the event study test for strategic default. Local linear regressions are executed at the contract level. In all cases our dependent variable is default or severely late payments, where lateness is defined as being at least 90 days past due. All regressions use an event study methodology, where an event is defined as a weekly price increase of at least 3%. We also test for the equality of coefficients between columns (1) and (4) and are able to reject equality, with a p-value = 0.0134. Appendix E reports further robustness checks. Standard errors are clustered by event-day bins. *** denotes significance at 99%; ** denotes significance at 95%; * denotes significance at 90%.

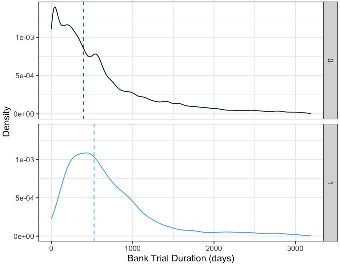
Calculate that 50% of default is strategic

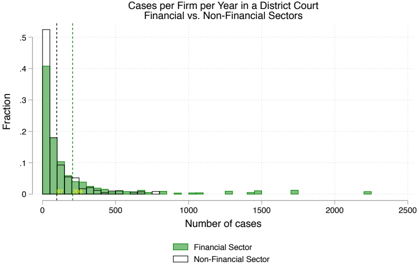
Inefficient Legal System Hinders Lending

Prevalence of moral hazard / strategic default $\implies$ monitoring and enforcement technologies central for credit supply.

- However, creditor protections often weak

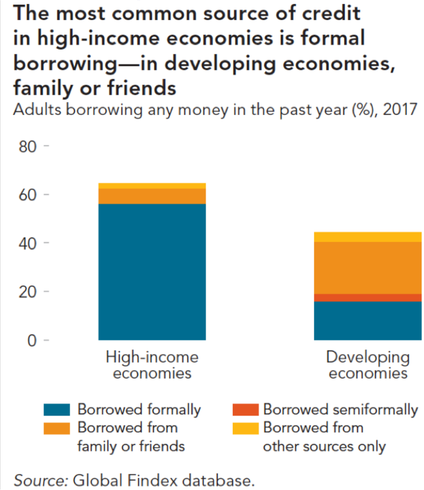
Rao (2022) argues that court inefficiencies in India suppress lending





Ponticelli and Alancar (2016) QJE show bankruptcy reforms in Brazil increase supply of secured loans (collateralized).

Implications for Credit Supply

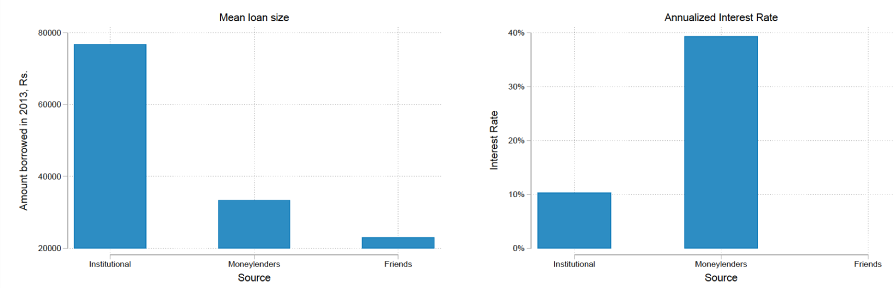


- Formal: financial institution/credit card
- Semiformal: e.g., savings club, not formal
- Family or friends: excludes those with formal or semiformal

Formal Loans vs. Moneylenders

Moneylenders important source of credit in developing countries

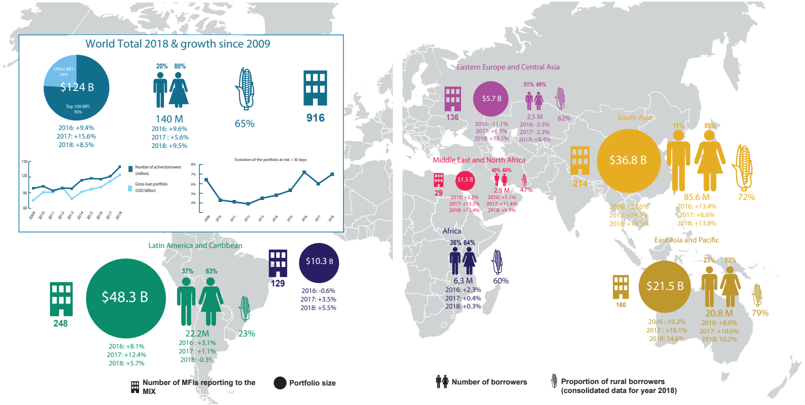
- Hard to discern in Findex exhibit - “other only” 4% of adults
- Misleading because HHs often take many types of loans



Source: Surendra (2020), data from India 2013 (NSS)

- Banks typically only serve wealthier clients (larger loans, lower interest)
- Moneylenders make larger loans than friends, smaller than formal, high interest
- Typical moneylender loans: no collateral, high monitoring

Microcredit Rare Formal Product to Achieve Scale



Source: Microfinance Barometer 2019

Microcredit Contract Features

Typical Contract Features:

- Typically small loans (India starting size of $\approx$ \$200)
- Collateral-free
- Borrowers tend to be women
- Fixed, regular repayment schedule (e.g.., weekly, monthly)
- Ability to obtain new, often larger loan upon repayment
- Homogenous loan product with only basic screening
- Historically, some type of group structure

At a basic level, microfinance "works":

- Typical borrower underbanked by formal sector
- Extremely low default rates, scalable (waves of VC funding)
- Rare private sector win

Low default rates indicate that microfinance has found a way to "solve" the moral hazard problem"

Roadmap

Returns to Credit

Positive effects of expansions of bank lending in India (natural experiments)

- Bank Branch Expansions:
    - Burgess and Pande (2005): reductions in poverty headcounts
    - Cramer (2023): improvements in health, expansions of health enterprises
- Banerjee and Duflo (2014): expansion of subsidized credit supply to SMEs $\implies \uparrow$ sales and profits

Large returns to capital for small businesses in Sri Lanka

- Classic paper by de Mel, McKenzie and Woodruff (2008)
- Randomize cash drops (\$100-\$200) to small firms
- Return to capital (real) 4.6% - 5.3% per month (55% - 63% per year)

Returns to Microcredit?

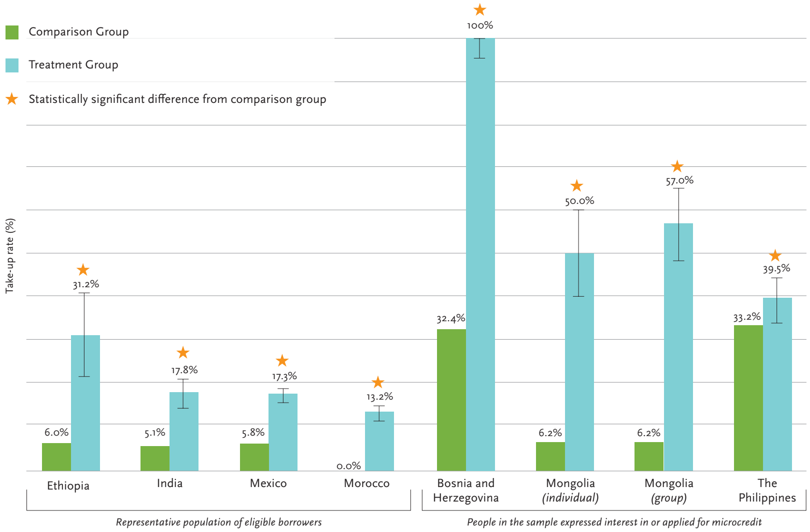
Seven(!) RCTs launched by different researchers between 2005 and 2010:

- Range of countries: Ethiopia, India, Mexico, Morocco, Bosnia, Mongolia, Philippines
- Urban and Rural examples
- Group and individual loans

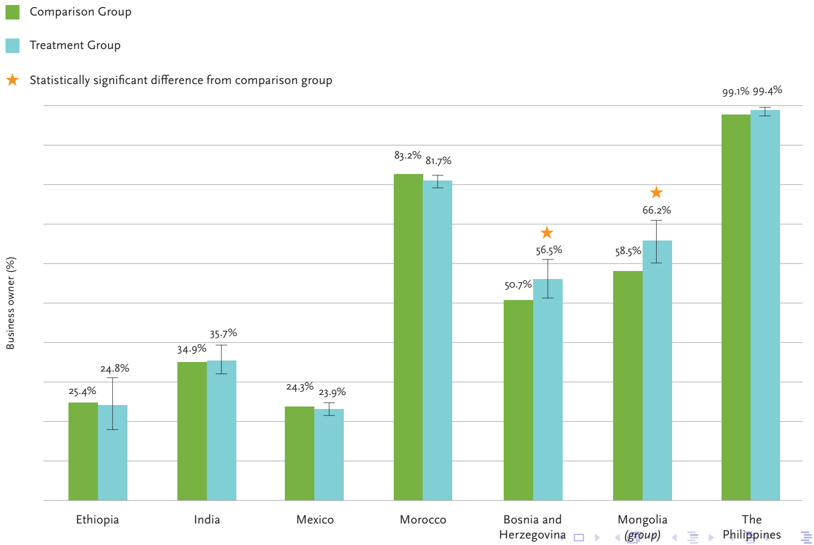
Studies primarily set up to measure causal impacts of microfinance on businesses

- MFIs pushed business growth narrative
- Outcomes include business profits, revenues, inputs, consumption, asset accumulation, women's empowerment
- Outcomes measured 12-18 months after treatment
- Allows for measurement of benefits from investing the loan proceeds (i.e., entrepreneurship narrative)
- Some studies have longer-run follow-ups, 3-year outcomes.

Results: Take-Up (source: JPAL)



Results: Business Ownership (source: JPAL)



Results: Other Key Outcomes (source: JPAL)

Outcome	Bosnia and Herzegovina	Ethiopia	India	Mexico	Mongolia	Morocco	Philippines
Business ownership	↑	—	—	—	↑	—	—
Business revenue	—	—	—	↑	—	↑	—
Business inventory/assets	↑	*no data*	↑	*no data*	↑	↑	—
Business investment/costs	—	—	↑	↑	*no data*	↑	↓
Business profit	—	—	—	—	—	↑	—
Household income	—	—	—	—	—	—	—
Household spending/consumption	—	↓	—	↓	↑	—	—
Social well-being	—	—	—	↑	—	—	↓

Putting these Results Together

- Rachael Meager analyzed the results in a meta-analysis, still nothing on profits
- Studies designed to test idea that microfinance solves credit constraints, allows small businesses to thrive
- Some of the funds are used for businesses, but overall, no huge detectable impacts on businesses

Borrowers must be spending the money, but 18 months later, can't see any lasting business or consumption benefits

Demand for Finance

In principle, credit could be beneficial for three key reasons:

1. Business investment
2. Bringing lumpy consumption forward (savings vs. credit cycles)
3. Mitigating risks

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3. Mitigating risks

MF findings:

- Modest impacts on 1, not transformational
- No test of 2, but completely possible given patterns of asset accumulation
- (Unreported results): null impacts on consumption variability.
    - MF contract structure ill-suited for this. Inflexible, immediate repayment, continuing cycles.

Scope for Any Transformative Impacts?

No smoking gun evidence for the average borrower:

- Short-run RCT evidence: +ive impacts on business investment, but no detectable impacts on profits, cons.

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Impacts likely heterogeneous for numerous reasons (Meager 2019).

- In Hyderabad, only 49.7% of MF borrowers have *any* business $\Longrightarrow$ many borrow for consumption, not business growth.
- MF may cause weaker businesses to enter
- MF loans might not be large enough to push many entrepreneurs out of low steady state (Bandiera et al 2020)

$\Rightarrow$ Investment impacts likely most relevant for:

- "Gung-ho" entrepreneurs (GEs), borrow to scale businesses
- In Banerjee et al (2022), we use a simple proxy: did household choose to enter entrepreneurship *before* microfinance was widely available?

Setting: Banerjee et al (2022)

We use the RCT variation from Banerjee et al. (2015)

- 104 neighborhoods of Hyderabad selected by Spandana in 2005
- Spandana entered 52 neighborhoods **(treatment)** in 2006
- Spandana entered remaining neighborhoods **(control)** in 2008
- Andhra Pradesh (AP) ordinance outlawed microfinance in 2010 $\implies$ all neighborhoods lost access

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Surveys:

- (Partial) baseline in 2005
- Endlines in 2007 and 2010 (analyzed in Banerjee et al 2015)
- Longer-run endline in 2012, analyzed here.

Exposure to microfinance

	(1) Borrowed from MFI in last 3 years (EL1 1)	(2) Borrowed from MFI between 2004-10	(3) Outstanding MFI loan (EL 2)	(4) Total MFI loan amt (EL2)	(5) Informal credit (EL3)
Panel A: Exposure to credit					
Treatment	0.109***	0.044*	0.008	946.417**	2668.157
	(0.022)	(0.024)	(0.020)	(474.365)	(3545.218)
Control Mean	0.256	0.498	0.332	6670.434	57151.686
Control Std. Dev.	0.436	0.500	0.471	13627.432	1.13e+05
Observations	6804	5467	6143	6143	5744
Panel B: Exposure to credit by entrepreneurial status					
Treatment	0.109***	0.036	0.003	677.234	-1683.957
	(0.021)	(0.026)	(0.021)	(508.180)	(4226.917)
Treatment $\times$ GE	-0.002	0.020	0.013	754.962	14085.007*
	(0.030)	(0.032)	(0.031)	(929.289)	(7387.176)
Gung-ho entrepreneur (GE)	0.163***	0.110***	0.093***	2557.957***	3647.067
	(0.023)	(0.022)	(0.020)	(671.712)	(5833.084)
Treatment + Treat $\times$ GE	0.107	0.057	0.016	1432.197	12401.050
P(Treat + Treat $\times$ GE $\neq$ 0)	0.001	0.091	0.617	0.102	0.046

Reduced form outcomes (EL3)

	(1) Has a business	(2) Total business assets	(3) Business profits	(4) Total wages paid	(5) Non-business durables
Panel A: Effects of credit					
Treatment	0.038*	1565.222***	576.774***	373.747***	351.696
	(0.020)	(426.789)	(179.375)	(133.018)	(239.737)
Control Mean	0.307	6680.551	2066.436	348.367	8482.853
Control Std. Dev.	0.461	20448.064	6039.441	4700.427	14264.700
Observations	5744	5744	5580	5736	5744
Panel B: Effects of credit by entrepreneurial status					
Treatment	0.024	816.198	263.906	275.264**	-175.322
	(0.018)	(526.966)	(168.567)	(118.604)	(323.643)
Treatment $\times$ GE	0.040	2325.597	1004.523**	311.864	1716.980**
	(0.028)	(1483.448)	(501.565)	(368.366)	(725.416)
Gung-ho entrepreneur (GE)	0.422***	8906.264***	3493.457***	488.639*	-513.234
	(0.020)	(973.087)	(350.655)	(266.816)	(563.800)
Treatment + Treat $\times$ GE	0.064	3141.795	1268.429	587.127	1541.658
P(Treat + Treat $\times$ GE $\neq$ 0)	0.008	0.011	0.004	0.093	0.007

Persistent effects of a "one-time" intervention...

Policy Implications

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. Why not?

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- Screening technologies can be expensive
- Homogeneous contracts allow MFIs to economize on costs
- Contracts that limit risk-taking improve repayment
- Roth (2017): MFIs don't have incentives to segment this market

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

How could financial institutions do better?

What types of products might be better for:

- Gung-ho entrepreneurs?
- Reluctant or non- entrepreneurs?

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- Gung-ho entrepreneurs?
- Reluctant or non- entrepreneurs?

One possibility:

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

Roadmap

1. Mobile Money
2. Credit: Why is Lending So Hard?
3. Returns to Credit Expansions
4. Equilibrium Effects of Credit Access
5. Improving Credit Product Design
6. Digital Finance

How Does Microfinance Aggregate Up?

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

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1. facilitate entrepreneurship and job creation (e.g., Evans and Jovanovic 1989, Banerjee and Newman 1993)
   - $\Rightarrow$ *Business finance channel*

How Does Microfinance Aggregate Up?

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.

Breza and Kinnan (2021) "Measuring the Equilibrium Effects of Credit" QJE measure the equilibrium impacts of MF using a large political shock as a natural experiment.

Breza and Kinnan (2021)

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

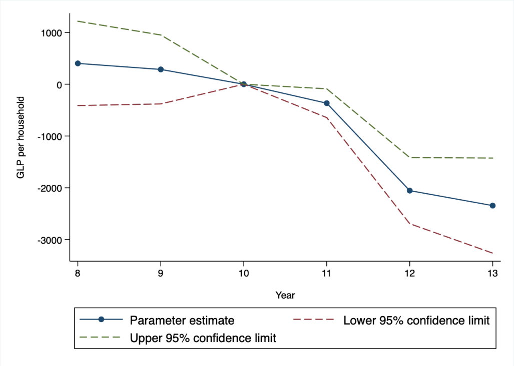
- Wiped approx. $1 billion out of the Indian microcredit market
- Impacts of crisis heterogeneous across lenders depending on portfolio in affected state (AP)

Focus on districts *outside* on AP (no direct effects, credit supply contraction through lender balance sheets)

- 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.

Change in Principal Outstanding: High vs. Low Exposure Districts



- No diff credit growth pre-ordinance (2010)
- $\downarrow$ \$25 in MF per rural HH in high exposure districts
- No change in bank / SHG credit

Equilibrium Effects: Labor & Consumption

	(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 × Post 2010	-6.432**	0.057	-0.446**	-86.227***	0.012
	(2.954)	(0.234)	(0.196)	(30.333)	(0.011)
Exposure Ratio × 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

	(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

- ↓ wages, total HH labor earnings, consumption
- Multiplier of 2.9
- Wage ↓ larger in non-tradable sectors (agg. demand)
- ↓ in HH biz investment, construction (both channels)

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

Roadmap

1. Mobile Money
2. Credit: Why is Lending So Hard?
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Bari et al 2021

Investigate how to deliver more financing to successful MF clients

- Context:
  - non-profit MFI in Pakistan, interest-free loans
  - Larger loans after repayment, up to cap of $\approx$ \$500
- New product idea: Hire-pay (rent-to-own) contract
  - Borrower 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%, borrower makes rental payments, by 18mos., buys out MFI
  - If breach of contract, MFI liquidates asset (usually difficult)
- RCT with successful prior borrowers
  1. Control: can take interest-free loan at cap $\approx$ \$500
     - 30% take up
  2. Treatment: Hire-purchase contract (2 variants)
     - 50% take up

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) 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

Prospects for segmenting the market

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

Possibilities:

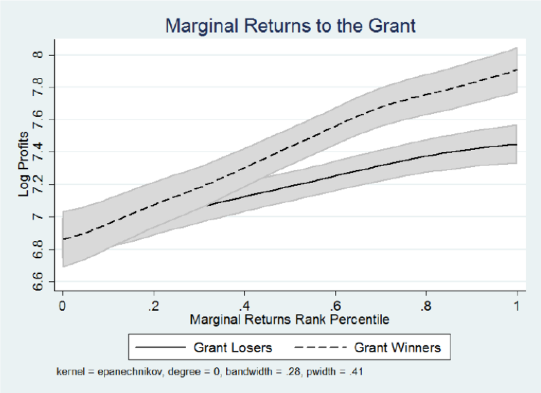
- Use new data sources + ML (will return to this, below)
- Use peer information more surgically than current status quo

What about peer screening?

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

- Do individuals have knowledge about the returns to capital of their peers?
- Context: 1,345 microentrepreneurs in Amravati, Maharastra India
- 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"
- Can compare treatment effects on grant winners (marginal returns to credit) by peer rankings

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! However, peers might lie if used for loan origination

Taking Stock

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 specific businesses

But, standard microfinance contracts might not work for some businesses

- Too rigid? Limits risk taking?

Another approach - redesign the microfinance contract.

Tweaking the Contract Structure

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

- Control: Status quo of weekly payments
- Treatment: Grace period of 1 month before first payment due

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: More Flexibility

Battaglia, Gulesci and Madestam: Let borrowers skip 2 payments.

	(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

	(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

- Similar business impacts, no ↑ default.
- Grace periods later in loan modestly *decrease* default

Intrahousehold Bargaining and Microfinance Returns

Do intrahousehold frictions limit benefits of loans?

- Bernhardt et al (2019) show that MF/capital drops have large effects when woman's business is only HH enterprise. (i.e., no competition with husband's biz for resources)

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- Bernhardt et al (2019) show that MF/capital drops have large effects when woman's business is only HH enterprise. (i.e., no competition with husband's biz for resources)

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

- Uganda: sharing rules within 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 (why?)
  - 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

Roadmap

1. Mobile Money
2. Credit: Why is Lending So Hard?
3. Returns to Credit Expansions
4. Equilibrium Effects of Credit Access
5. Improving Credit Product Design
6. Digital Finance

Expanding the Product Offerings: Credit

Recall two core frictions making it hard to expand credit supply:

- Moral hazard / strategic default, adverse selection

MM operators and telcos have some ability to mitigate both:

- Direct debit from mobile wallet
  - If borrower really wants to default, can't use mobile
- Data!
  - Telcos observe detailed call data: number, duration, distances, geog travel, predictability / variability
  - MM operators observe financial transactions: money in e-wallet, frequency of cash in/ cash out, # transfer partners

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Bjorkegren and Grissen (2020): mobile data predicts loan repayment

- Model with mobile predictors outperforms credit bureau data
- Mobile predictors as good for those with no credit record
- "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"

Mobile Money v2 Products

In 2012, M-Pesa launched digital, linked bank account: M-Shwari with popular loan product

- Small, short term loan (30 days), 7.5% monthly interest rate (expensive!)
- Qualify for first loan based on M-Shwari credit score
- Can qualify for bigger loans with established M-Shwari transaction history

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What are the impacts of such "fast" credit?

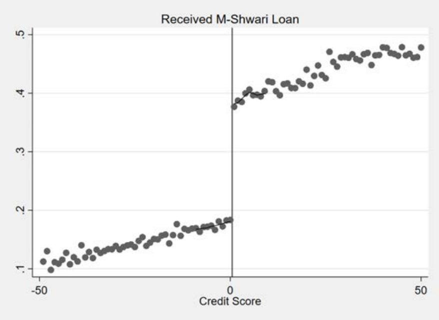
- Positive:
  - Super easy to get in a pinch
  - Could help households smooth shocks (PIH motive)
- Negative:
  - Will this just lead to a debt trap with never-ending, mounting interest payments?

Bharadwaj et al (2019): Results

Bharadwaj et al (2019) evaluate the M-Shwari loan product using RD design.

- Lending based on internal credit score + threshold (c=0)

Figure 2A: First Stage, Administrative Data



- Clear discontinuous jump in likelihood of getting a loan at threshold

Bharadwaj et al (2019): Results

	Shock	Expenses Foregone			
	(1)	(2) Any	(3) Meals	(4) Medical	(5) Non-Food
Bandwidth of -9 to 10					
Score Cutoff	0.013	-0.063**	-0.045	-0.049*	-0.020
	[0.018]	[0.030]	[0.032]	[0.029]	[0.032]
Sidak-Holm p-value			0.896	0.896	0.998
Control Mean	0.892	0.679	0.447	0.300	0.474
Observations	4136	3711	3711	3711	3711

- In the case of a shock, loan allowed HHs to not have to cut consumption

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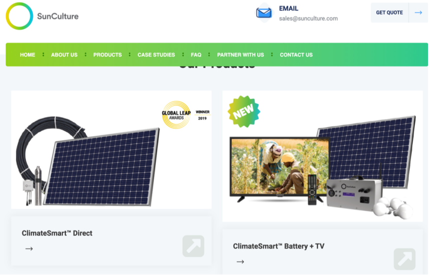
Brailovskaya et al (2021) worried about harms from fast credit:

- Malawi RD evidence: No SR $\downarrow$ in financial well-being
- BUT, most don't repay on time and rack up high fees
- Randomize phone-based financial literacy program: $\uparrow$ repayment speed, but $\uparrow$ loan demand $\implies$ $\uparrow$ total default

Question: is this another place where savings is the better product?

Digital Collateral

Gertler, Green and Wolfram (2021)



- Solar-powered water pump (left), Solar-powered battery w/ TV and lightbulbs (right)
  - Assets are expensive: need to provide financing to stimulate demand, but offering credit to low SES HHs hard
  - Solution: Pay for asset over time via mobile money, disconnect asset remotely in case of non-payment
- Can go one step further. Once asset is paid off, can use it as collateral. Threat of disconnection to provide repayment incentives

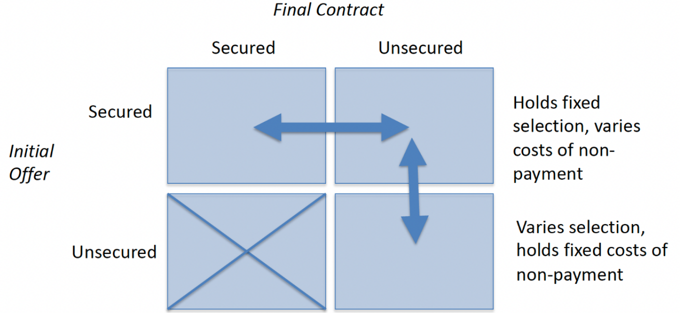
Digital Collateral: Experimental Design

Product: \$81 cash loan for school fees in Uganda

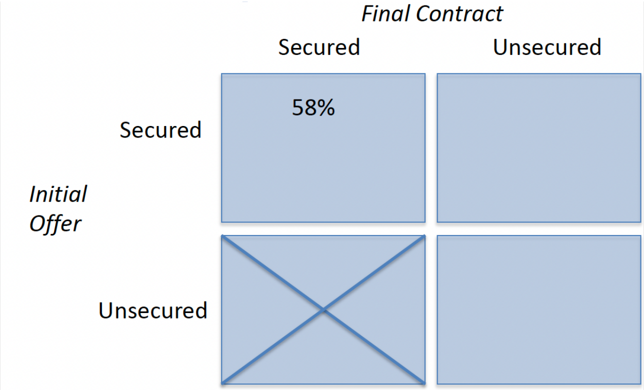
- Offered to existing customers who had repaid initial loan on solar home system, expanded eligibility, larger loans
- Unsecured and secured versions, daily payment
  - Secured - can shut off SHS if non-repayment, 7% lower take-up

Design based on Karlan and Zinman (2009)

- Surprise some offered secured with unsecured

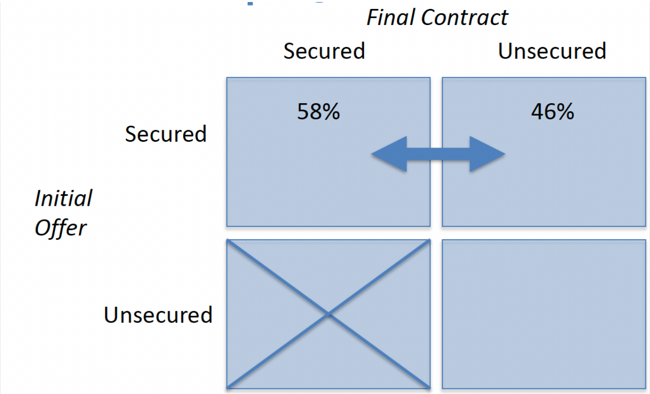


Digital Collateral: Results - Repayment



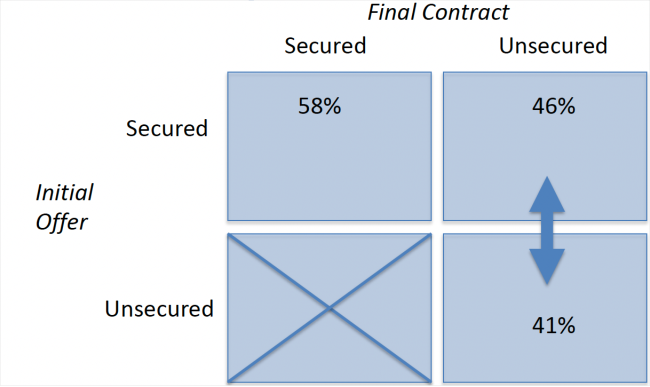
- Secured loan: 58% full repayment by 150 days

Digital Collateral: Results - Repayment



- Holding offer fixed (i.e., selection), secured loan has 12% more repayment than unsecured (statistically significant)
- Consistent with DC improving moral hazard

Digital Collateral: Results - Repayment



- Holding final unsecured loan terms fixed, those who selected into a secured loan have 5% better repayment (though not significant)
- However, even secured loan unprofitable for lender

Digital Collateral: Considerations

Benefits to borrowers:

	Enrollment		Days absent		Log school expenditures		Education index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	0.09***		-1.83**		0.37**		0.32***	
	(0.03)		(0.72)		(0.15)		(0.10)	
Secured (β_1)		0.11***		-2.39***		0.47***		0.39***
		(0.03)		(0.77)		(0.16)		(0.10)
Surprise Unsecured (β_2)		0.08***		-1.31*		0.32**		0.27***
		(0.03)		(0.74)		(0.15)		(0.10)
Unsecured (β_3)		0.10***		-2.00***		0.37**		0.33***
		(0.03)		(0.74)		(0.15)		(0.10)
Pooled × Number of School-Aged Children	-0.02***	-0.02***	0.38**	0.37**	-0.05	-0.05	-0.06**	-0.06**
	(0.01)	(0.01)	(0.19)	(0.19)	(0.04)	(0.04)	(0.02)	(0.02)
Outcome control mean	0.88	0.88	2.77	2.77	81	81	0	0
p-value for $\beta_1 = \beta_3$		0.51		0.34		0.24		0.28
n	1683	1683	1683	1683	1683	1683	1683	1683

Costs to borrowers:

- Median customer locked out for $\frac{1}{3}$ of days
  - Might not worry about running TV, but more problematic if earnings suffer (need to be careful with application)
- No evidence of asset sales or additional borrowing to repay

Can make product sustainable by not lending to riskiest $\frac{1}{3}$

- Riskiest $\frac{1}{3}$ drive bulk of shut-out (66% of days)

New Models for Digital Payments

- Digital payments growing quickly
- Driving/unlocking innovation in Fintech
- Government-Driven Approach: Brazil and India

Mobile payments + Add to myFT

Brazil counts success with Pix payments tool

State-backed instant transfer service is credited with helping to widen financial inclusion

Payments record: Pix hit a single-day high of 153mn transactions that moved R$76bn ($15.3bn) in September 2023 © Rafael Henrique/Zuma Press/Alamy

Where Digital Payments, Even for a 10-Cent Chai, Are Colossal in Scale

India's homegrown instant payment system has remade commerce and pulled millions into the formal economy.

Share full article

A QR code at a roadside food stall in Mumbai, India, allows customers to make instant payments with their phones. Atul Loke for The New York Times

Digital Finance: Thoughts

- Mobile money and FinTech have been able to reach a large segment of unbanked individuals
- Exciting potential to address credit market frictions
- Key challenge: regulatory framework that lets these platforms grow but also protects consumers
- The promise for digital payments goes beyond p2p transfers
  - Impact on firms and supply chains understudied
- Likely that these types of platforms will be engines for more financial innovation
- Different approaches in different countries
  - Kenya/Bangladesh model: private mobile money operator, substantial market power (Brunnermeier, Limodio, Spadavecchia 2023)
  - India/Brazil: government digital payment rails with full interoperability with bank accts/ digital wallets (UPI/PIX)
  - More work needed to understand pros and cons