The real cost of credit constraints: Evidence from micro-finance

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The growing importance of micro-finance

- Pay-day lending and micro-finance have grown in popularity in the last 20 years.
  – Help ease liquidity constraints and enable consumption smoothing
- However, adverse effects of borrowing: over-borrowing, time-inconsistent preferences, financial distress.
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- Concerns exacerbated by alleged predatory lending practices and usurious interest rates.
- Policy questions on the usefulness of such credit. Restrict access in some cases.
- Evidence on interventions is mixed.
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This paper

- Policy intervention in Andhra Pradesh (AP) that forced a closure of the micro-finance industry
- Data from ‘Consumer Pyramids’, which releases average household characteristics of about 200 geographical regions across India
- Allows us to ask how micro-credit withdrawal affects consumption:
  1. Is average household consumption affected when access to micro-finance is reduced?
  2. Does the volatility of average consumption change?
  3. Which households are more affected?
- Causal effect of the ban calculated as the difference-in-difference of the average household consumption between the treated regions (in AP) and the controls (matched regions outside AP).

What we find

- Average consumption expenditure of households in AP *decreased* by 19.5 percent.
- Volatility of average consumption expenditure after *increased* after the ban.
- There was a larger negative impact for households with liquidity constraints.

Part I

Research setting: Policy and data

The micro-finance ban in Andhra Pradesh

- One of the larger states in India, AP was the locus of growth of the Indian micro-finance industry, starting from the '80s.
- In 2010, there was an estimated 27 million customers of micro-finance in a population of 84 million.
- In December 2010, the state government passed a law that imposed operational constraints on the micro-finance institutions (MFIs).
- Micro-finance came to a standstill in AP; default probabilities went up to near 100%.
  Outside AP, micro-finance loan portfolios rose by 25 percent.
- An estimated credit shortfall of about Rs.30 billion to households (Srinivasan, 2012).

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Database: Consumer Pyramids

- Household panel survey, run every quarter.
- 150,000 households included in the survey.
- Geographical breakup at the level of multiple regions within the Indian states called Homogenous Regions (HR).
- Data released as average for households in an HR.
- Additional available data used in this study:
  - Averages by income categories (I-1, highest income, to I-9, lowest income)
  - Identification of HRs as rural and urban.
- 14 HRs with $\sim$ 13,000 households in AP.
  82% of AP households borrow.

Part II

Research design

Approach

- Step 1: Calculate the average household consumption in AP before the ban, and compare it with the average household consumption after the ban.
- Step 2: Identify regions in India which are similar to the AP HRs, but where the ban was not in effect.
- Step 3: Compare the change in the average AP household consumption before and after the ban to the change in the average household consumption of these matched HRs in the same period.
- If there is a significant difference between the change in AP consumption and the change in the consumption of the matched regions, we attribute it to the ban.
- Step 4: Worry about threats to validity.
  Did something else cause the change in the average consumption in AP?

Matching methodology

- Match on income and socio-economic factors:
  1. Average household income.
  2. Number of households.
  3. Working population (The proportion of the HR that is between 20 and 60 years).
  4. The proportion with graduates past the 10^{th} grade.
  5. The proportion that is financially excluded (the fraction of households with a bank account / credit card / life insurance policy / other similar formal financial products).
  6. The proportion of farmers in the region.
- Exclude the HRs in the states of South India – Tamil Nadu, Kerala and Karnataka – which might have suffered from spillovers of the ban
- Mahalonobis distance measure for nearest neighbour matching

$$D_{ij} = \left[(X_i - X_j)'\Sigma^{-1}(X_i - X_j)\right]^{\frac{1}{2}}$$

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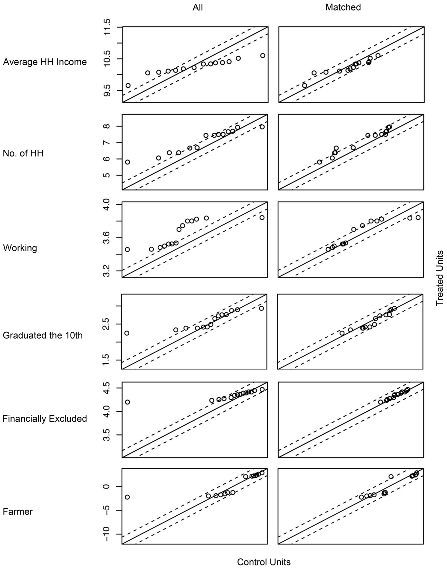
QQ plots for match balance



The difference-in-difference (DID) estimator

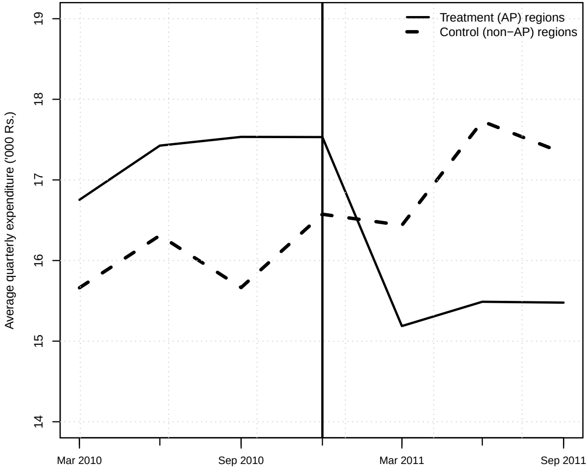
$$C_{i,t} = \beta_0 + \beta_1 \text{AP}_{i,t} + \beta_2 \text{POST-CRISIS}_{i,t} + \beta_3(\text{AP}_{i,t} \times \text{POST-CRISIS}_{i,t}) + \epsilon_{i,t}$$

- AP is a dummy which takes value “1” if *i* is a region in AP (the treatment region) and “0” otherwise (the control region)
- The PRE-CRISIS quarters include the four quarters of March, June, September and December 2010.
- POST-CRISIS includes the four quarters of March, June, September and December 2011
- Coefficient of interest: β_3.

Part III

Results

Average consumption



DID results: Average consumption

	$\hat{\beta}_3$	std.err.	p.val	Adj.p	Q_{power}
Total	**-3375.1**	**1450.5**	**0.02**	**0.05****	6000
Food	-1302.6	419.1	0.00	0.01***	2000
Fuel	-504.8	199.3	0.01	0.05**	1000
Education	-350.3	151.8	0.02	0.05**	500
Cosmetics	-165.1	68.3	0.02	0.05**	300
Miscellaneous	-341.5	733.3	0.64	0.80	2000
Communication	12.3	98.3	0.90	0.91	500
Clothing	-431.4	126.9	0.00	0.01***	500
Transport	-25.9	44.6	0.56	0.80	400
Intoxicants	-222.7	49.1	0.00	0.00***	200
Rent	-14.2	127.2	0.91	0.91	300
EMIs	31.5	63.9	0.62	0.80	500
Restaurant	-82.3	71.1	0.25	0.46	400
Health	17.8	58.6	0.76	0.88	200
Recreation	-24.6	24.7	0.32	0.53	100

*** indicates 1% and ** indicates 5%

Summarising results

- Average consumption of all households in AP *decreased* after the ban.
- Volatility of consumption in AP *increased* after the ban.
- Liquidity constraints matter?
  Poorer households and households in *rural regions* (with lower access to alternative finance) saw a *larger drop* in consumption.

Part IV

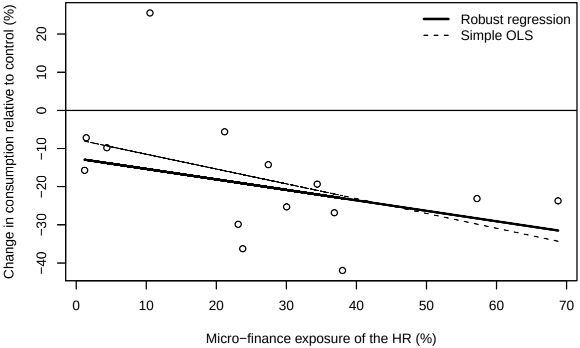
Threats to validity

Threats to validity

- Events other than the ban caused the results.
- The results are sensitive to the matching strategy.
- The quality of matches is poor because South India, where other states are as indebted as AP, was excluded from the control pool.

Did events other than the ban cause the results?

Impact of the ban by micro-finance exposure



Did a drop in income cause the results

$$\text{Inc}_{i,t} = \beta_0 + \beta_1 \text{AP}_{i,t} + \beta_2 \text{POST-CRISIS}_{i,t} + \beta_3 (\text{AP}_{i,t} \times \text{POST-CRISIS}_{i,t}) + \epsilon_{i,t}$$

$\hat{\beta}_3$	std.err	p.val	adj.p
-2119.82	2456.23	0.39	0.61

Sensitivity to matching strategy

- Dropping one covariate at a time.
- Genetic matching algorithm.
- Adding the proportion of women.
- Adding South Indian states in the list of available controls.
- The results do not change.

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Part V

Conclusion

Summary of the results

- Results suggest a fairly large negative impact of the ban on micro-finance.
  – Consumption dropped by 19.5 percent over the first four quarters after the micro-finance ban.
- Impact visible across all income classes – including those which use little micro-credit themselves.
  Suggests general equilibrium effects.
- The effect is observed on both the level as well as the volatility of consumption.
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Future research

- Drawback of the analysis is that we do not observe individual household level records.
- Such record level data may reveal that welfare is improved without micro-finance, for *certain* households.
- With the release of record level data, these effects could be measured.

Thank you
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