### The Economic Effects of a Borrower Bailout: Evidence from an Emerging Market

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EMF Mumbai, December 20, 2013

## Motivation

## What do economic stimulus programs do?

- Economic stimulus programs have a long history
  - ightarrow Great Depression and New Deal Era in the United States
    - → Direct subsidies to stimulate demand
    - ightarrow Debt moratoria and restructuring programs
  - ightarrow Examples from the recent financial crisis:
    - ightarrow Direct subsidies for investment or consumption
    - → Credit market interventions
    - → Tax policy
- But effects on economic activity remain poorly understood
  - → Effects on real economic activity
  - → Time pattern of effects
  - → Externalities

### Motivation

### Stimulus programs through the credit market

- The case for interventions into debt contracts
  - ightarrow address credit constraints; stimulate investment and consumption directly
  - → Insurance against otherwise uninsurable aggregate shocks (Bolton and Rosenthal, 2002)
  - → mitigate deadweight losses from large scale default and foreclosure (Guiso, Sapienza and Zingales, 2009; Breza 2013; Giné et al 2013)
- The case against interventions into debt contracts
  - → Distort incentives for banks (Diamond and Rajan 2000; Gianetti and Simonov, 2009; Phillipon and Schnabl 2013)
  - → Distort contracting environment and incentives for borrowers
  - ightarrow may lead to ex-post credit rationing

## Contribution

### Use natural experiment to trace the effects of large stimulus program

- ▶ Stimulus enacted through an ex-post intervention in the credit market
  - → Provide causally identified evidence
  - ightarrow Quantify credit market *and* real effects

#### Moral hazard consequences

- Political interventions into debt contracts and moral hazard (Guiso, Sapienza and Zingales, 2009; Breza, 2013; Giné et al 2013)
  - → Estimate moral hazard costs directly
  - → Distinguish between impact on bank and borrower risk-taking

#### Interaction with the political cycle

- ▶ Political cycles in lending and loan performance (Dinç 2005, Cole 2009)
  - → Identify mechanisms perpetuating moral hazard

# Main findings

- Post-program credit supply: Indian districts with greater exposure to the bailout experienced a significant post-program slowdown in new lending.
- **Ex-post moral hazard:** Districts with a greater exposure to the bailout saw significantly faster growth in non-performing loans after the program.
- Bank versus borrower moral hazard: The results suggest that deterioration in loan performance is due to borrower- not bank moral hazard.
- Real effects: Our estimates on agricultural productivity identify a precise zero.
- Mechanism moral hazard and the electoral cycle: The program magnified default cycles around election years, suggesting the anticipation of politically motivated credit market interventions as a key mechanism that reinforces moral hazard in loan repayment.

India's Bailout for Rural Households

## The program

India's bailout for rural households

### Why is this an interesting program to study?

- Possibly the largest household level bailout program in history
- ▶ Economically significant
  - $\rightarrow$  US\$ 16 17 billion
  - $\rightarrow$  1.7 2% of India's GDP
  - ightarrow Benefit to approximately 50 million rural hoouseholds
- Representative of a common class of stimulus programs
  - → Ex-post restructuring of debt contracts
  - ightarrow Examples from the United States
    - → Debt moratoria in the 1930s
    - → Mortgage restructuring
  - → Examples from developing economies
    - → Thailand: US\$ 2.9 billion bailout for rural households
    - → Brazil: restructuring of more than US\$ 10 billion farm debt

# The program

India's bailout for rural households

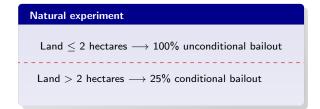
### The Agricultural Debt Waiver and Debt Relief Scheme (ADWDRS)

- ▶ Partial or full bailout of all agricultural loans outstanding and overdue
  - → Covers all ag loans originated Dec 31, 1997 Dec 31, 2007
  - → Loan must be 90+ DPD on February 28, 2008
  - → Loans at private, public sector, cooperative and regional rural banks
  - ightarrow Eligibility depends on land pledged as collateral
  - ightarrow Banks refinanced by the Reserve Bank of India
- What was the policymaker's motivation?
  - → Stimulate demand and investment
  - → Transfer to rural voters ahead of national elections
  - → Resolve accumulated bad loans in the books of state banks

India's bailout for rural households

### Identification challenge: endogeneity of program exposure

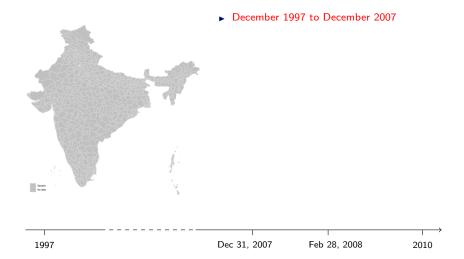
- ▶ Land-based eligibility rules generate exogenous variation in bailout exposure
- ▶ Benefit depends on land pledged as collateral several years prior to program
- ▶ Program rules were unanticipated, applied retrospectively
  - ightarrow no prior debt relief program based on landholding

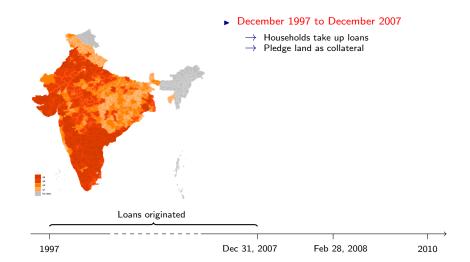


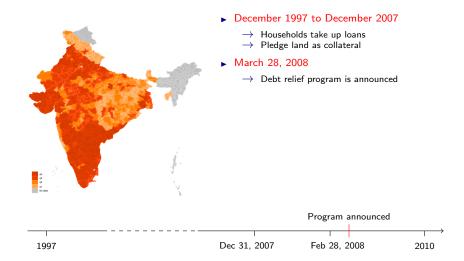
India's bailout for rural households

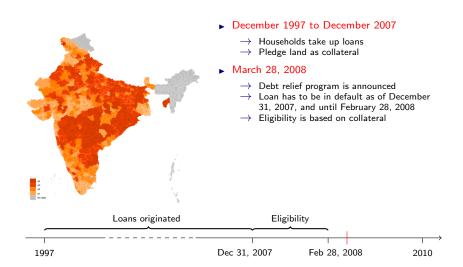
### Exogenous variation in program exposure

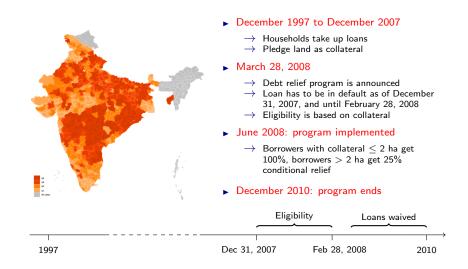
- Two sources of exogenous variation at the district level are key to our identification strategy:
  - A. Share of credit that is below collateral threshold and could have qualified is determined by a district's historical land distribution
  - B. Time series of weather shocks determines credit share actually in default











#### Overview

- ► Panel of 491 (of 593) Indian districts 2001-2012
  - ightarrow Data at the level of India's 2001 census districts
  - → Districts in the data account for
    - ightarrow 94% of the Indian population
    - ightarrow 89% of total bank credit in the base year
- Program exposure
  - → Amount of credit qualifying for the program
  - → Amount of debt relief claimed under the program
- Data on credit
- ▶ Data on loan performance
- Additional controls
  - → Rain, monsoon precipitation as percentage of long-run mean
  - → Electoral cycle

### District-level credit

- ▶ Panel of bank lending at the district level
  - ightarrow The Reserve Bank of India BSR dataset
  - ightarrow Data by district and type of credit
    - → Total credit,
    - ightarrow ag credit
    - → consumer credit
  - → Covers all commercial bank lending in India
  - → Based on census of loans at branch level
  - ightarrow Reported annually
- ▶ Panel of loan performance
  - → Based on proprietary data from India's largest four public sector banks
    - → agricultural credit and NPLs
    - → 27,678 branches in base year
      - → approximately 62% of rural credit

#### Additional controls

#### Rainfall, deviation from normal

- → Monsoon rainfall (variation in credit demand)
  - ightarrow as percentage of 50 year district average
  - → Indian meteorological department data
  - ightarrow District level gauge data for coverage to 2011
  - ⇒ control for variation in credit demand

### Electoral cycle

- ightarrow state elections are staggered in time
  - $\rightarrow$  5 year election cycle
  - ightarrow state governments can call early elections
  - $\rightarrow$  full set of election dummies  $\sum_{t=0}^{4} e_t \operatorname{Program}$  exposure
  - → years until next scheduled state election
  - ⇒ control for political cycles in credit

Reduced form difference-in-differences

### Estimating equation: credit growth

$$y_{dt} = \alpha + \gamma \left( \mathsf{Bailout\_share} \cdot \mathsf{post} \right) + \delta_d + \vartheta_t + \mathbf{X}' \psi_{dt} + \epsilon_{dt}$$

- Difference-in-Differences (DD) around program date
- Three specifications
  - 1. District fixed effects and year dummies
  - 2. Regional credit cycles  $\Rightarrow \delta_d * region_k$
  - 3. Unit time trends
- ▶ Additional controls: rain, electoral cycle dummies

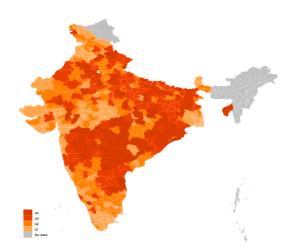
Identification

### Program exposure

$$extit{Bailout\_share} = rac{(1-\eta)\Big[ extit{credit}_{dar{t}}^{ extit{S}} + .25ar{\kappa} extit{credit}_{dar{t}}^{L}\Big]}{ extit{Total\_credit}_{dar{t}}}$$

- where  $1 \eta$  is the share of non-performing loans
- credit<sup>S</sup> is the amount of credit below the collateral threshold
- ▶ credit<sup>L</sup> is the amout of credit above the collateral threshold
- ▶ Let  $\kappa = 1$ , estimate ITT effect

Identification



Identification

### Summary statistics

	Bailout share [N=489]
Mean	.326
Median	.284
StDev	.224
Min	.002
Max	.991

▶ Bailout share by state

Effects of the Bailout

## T1 Effect on credit supply

Intensive and extensive margin

		$Log(credit_{dt})$						
	△ Amount			△ Accounts				
	(1)	(2)	(3)	(4)	(5)	(6)		
Bailout_share*post	-0.025** [0.013]	-0.024* [0.014]	-0.102*** [0.021]	-0.018 [0.012]	-0.025** [0.013]	-0.037* [0.022]		
# observations # clusters	4,941 489	4,941 489	4,941 489	4,941 489	4,941 489	4,941 489		
R-squared	0.909	0.912	0.921	0.700	0.717	0.716		
Year fixed effects	Yes	No	No	Yes	No	No		
Year*region effects	No	Yes	No	No	Yes	No		
District time trends	No	No	Yes	No	No	Yes		

- Persistently lower credit in high-bailout districts
- Bank lending slows down in districts with high program exposure
- Consistent with "evergreening" in pre-bailout period [Peek and Rosengren, 2005]







## T1 Effect on credit supply

Intensive and extensive margin

		$credit_t/credit_{2001}$						
	Δ Amount			△ Accounts				
	(1)	(2)	(3)	(4)	(5)	(6)		
Bailout_share*post	-0.138*** [0.027]	-0.138*** [0.030]	-0.251** [0.123]	-0.055* [0.031]	-0.066** [0.032]	-0.097 [0.091]		
# observations # clusters	4,918 489	4,918 489	4,918 489	4,918 489	4,918 489	4,918 489		
R-squared	0.182	0.285	0.107	0.107	0.141	0.081		
Year fixed effects	Yes	No	No	Yes	No	No		
Year*region effects	No	Yes	No	No	Yes	No		
District time trends	No	No	Yes	No	No	Yes		

- ▶ Persistently slower credit growth in districts with high program exposure
- ▶ Consistent with "evergreening" in pre-bailout period [Peek and Rosengren, 2005]







## T2 Effect on credit supply

Is there active reallocation?

		$credit_t - credit_{t-1}$						
	Low-bailout districts			High-bailout districts				
	(1)	(2)	(3)	(4)	(5)	(6)		
Eligible_amount*post	0.677*** [0.120]	0.465*** [0.134]	1.280*** [0.137]	0.097* [0.057]	0.061* [0.034]	0.161 [0.099]		
# observations # clusters (districts) R-squared	2,478 224 0,288	2478 224 0.344	2,478 224 0,438	2,451 224 0,263	2,451 224 0,414	2,451 224 0.344		
Year fixed effects Year*region effects	Yes No	No Yes	No No	Yes No	No Yes	No No		
District time trends	No	No	Yes	No	No	Yes		

- ▶ Significant reallocation of credit in the post-program period
- ▶ \$ 1.3 of new lending for every \$ 1 of debt relief in low-bailout districts
- ▶ \$ .16 of new lending for every \$ 1 of debt relief in high-bailout districts
- ▶ Post-program bank lending goes to observably less risky districts

## T3 Effect on loan performance

			<b>1</b> if ∆	NPA > 0			
		All districts			High bank competition		
	(1)	(2)	(3)	(4)	(5)	(6)	
Bailout_share*post	0.074*** [0.021]	0.088*** [0.022]	0.080* [0.048]	0.092*** [0.033]	0.075** [0.033]	0.240*** [0.072]	
# observations # clusters	2,676 489	2,676 489	2,676 489	1,402 237	1,402 237	1,402 237	
R-squared	0.243	0.276	0.297	0.214	0.253	0.305	
Year fixed effects	Yes	No	No	Yes	No	No	
Year*region effects	No	Yes	No	No	Yes	No	
District time trends	No	No	Yes	No	No	Yes	

- ▶ What is the impact on moral hazard in loan repayment?
- ▶ Bank lending becomes more conservative, new credit goes to lower risk borrowers
- ▶ But: unambiguous post program decline in loan performance in high-bailout districts

# T4 Real effects: productivity

### Revenue per hectare

- Key motivation of bailout programs
  - → stimulate demand and investment directly
  - → resolve debt overhang, disincentives for productive investment
  - → limited evidence that stimulus programs achieve this (Mian and Sufi, 2012)
- ▶ Test using district panel of agricultural productivity
  - $\rightarrow$  Crop yields for 20 most common crops in India (yield r, area a)
  - ightarrow Wholesale prices of agricultural commodities in base year 2001  $ar{p}$
  - → Panel 2001-2011

$$\pi_{dt} = \frac{\sum_{dt}^{C} \{r_{dt}^{c} \cdot \bar{p}_{d,2001}^{c}\}}{\sum_{d}^{C} a_{d}^{c}}$$

## T4 Real effects: productivity

### Revenue per hectare

			Log revenue	per hectare		
	(1)	(2)	(3)	(4)	(5)	(6)
Bailout_share*post	0.004	0.004	0.001	0.003	0.004*	0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
# observations	4,241	4,241	4,241	4,182	4,182	4,182
# clusters	488	488	488	488	488	488
R-squared	0.098	0.181	0.411	0.105	0.187	0.396
Year fixed effects	Yes	No	No	Yes	No	No
Year*region effects	No	Yes	No	No	Yes	No
District time trends	No	No	Yes	No	No	Yes

- ▶ No significant effect of bailout on agricultural productivity
- ▶ Debt relief does not resolve debt overhang; increase productivity
- Consistent with micro-evidence

Mechanism: Moral Hazard and the Electoral Cycle

### Mechanism

Moral hazard and the electoral cycle

- ▶ State elections in India
- Electoral cycle affects incentives for default
  - → Promises of Ienient enforcement (Examples: Haryana, Uttar Pradesh)
  - → Political interventions into the credit market (Andhra Pradesh)
- ▶ Political cycles in credit and default
- ▶ Was this mechanism magnified by the program?

## T5 Mechanism

### Moral hazard and the electoral cycle

			1 if ∧ N	NPA > 0		
		All district		High bank competition		
	(1)	(2)	(3)	(4)	(5)	(6)
Years_to_election*post	-0.011	-0.035**	-0.154***	-0.023	-0.051**	-0.120***
	[0.014]	[0.017]	[0.012]	[0.021]	[0.026]	[0.017]
#observations	2,913	2,913	2,913	1,506	1,506	1,506
R-squared	0.234	0.273	0.344	0.208	0.257	0.324
			Log lo	an size		
Years_to_election*post	-0.004	-0.004	-0.009	-0.003	-0.005	-0.008
	[0.006]	[0.009]	[0.006]	[800.0]	[0.012]	[0.007]
# observations	2205	2205	2205	1155	1155	1155
R-squared	0.467	0.490	0.748	0.516	0.549	0.767
Year fixed effects	Yes	No	No	Yes	No	No
Year*region effects	No	Yes	No	No	Yes	No
District time trends	No	No	Yes	No	No	Yes

- ▶ Significant negative effect on loan performance
- ▶ Effect due to borrower moral hazard; no change in loan size around elections
- ▶ Time pattern: effect persistent over time. Do borrowers "learn" to expect renegotiation?

## T5 Mechanism

### Moral hazard and the electoral cycle

		<b>1</b> if Δ NPA >	> 0
Model 1	(1)	(2)	(3)
Years_to_election*post	-0.011	-0.035**	-0.154***
	[0.014]	[0.017]	[0.012]
# observations	2,913	2,913	2,913
R-squared	0.234	0.273	0.344
Model 2			
Post*Years_to_election	-0.006	-0.008	-0.010
*Bailout_share	[0.011]	[0.012]	[0.014]
# observations	2,205	2,205	2,205
R-squared	0.255	0.284	0.370
Model 3			
Post*Years_to_election	0.271	-0.296	0.638
*Bailout_per_capita	[1.082]	[1.127]	[1.213]
# observations	2,205	2,205	2,205
R-squared	0.261	0.283	0.377
Year fixed effects	Yes	No	No
Year*region effects	No	Yes	No
District time trends	No	No	Yes

## Conclusion

# Summary

- Bailout has significant impact on the allocation of credit and post-program moral hazard
- We distinguish bank from borrower moral hazard. Bank lending after the bailout becomes more conservative: no extensive margin lending to high-bailout districts
- Strong negative effect on loan performance. One standard deviation increase in bailout leads to 7-10% faster growth in non-performing loans. Effect persists
- Estimates on productivity identify a zero effect
- Mechanisms: bailout amplifies default-cycles around elections, reinforcing and the effect of the bailout on borrower moral hazard

Thank you!

## Indian census districts

