Safety Nets, Credit, and Investment: Evidence from a Guaranteed Income Program

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NBER-ISB Fall 2022 Meeting
December 17, 2022

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    - New Dimension: Effect of guaranteed income on investment
  - Focus: Can it unlock untapped investment opportunities?
    - But, no direct evidence (Banerjee, Niehaus & Suri, 2019)

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Does guaranteed income encourage investment? If so, how?

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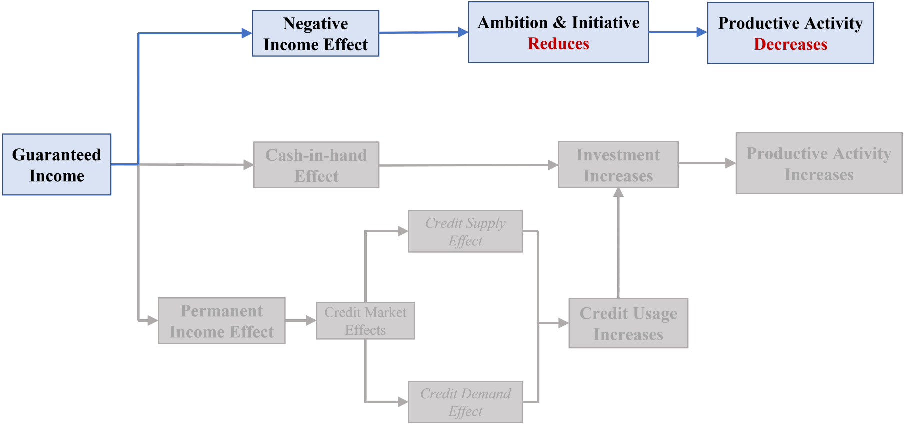

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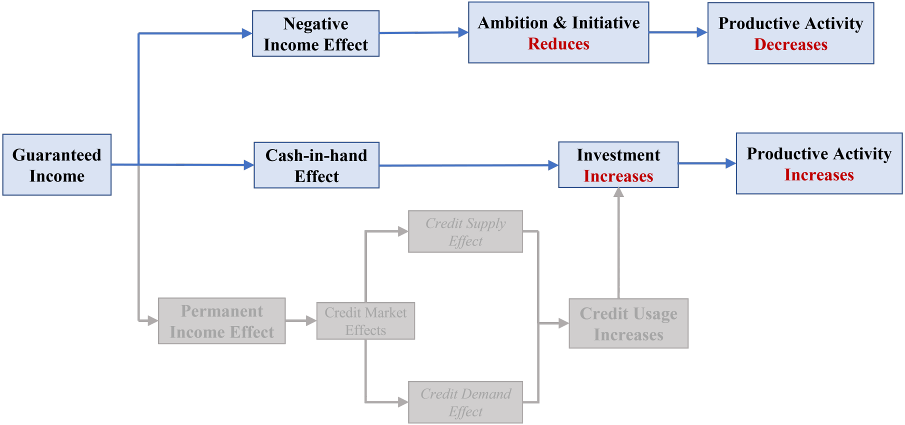

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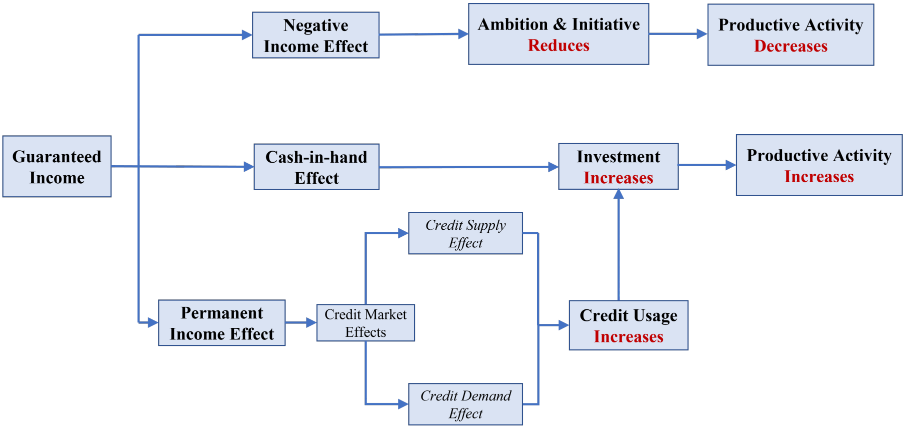

This Paper

- **Setting & Data**
  - A large natural experiment that gives unconditional & perpetual guaranteed income to all landowning farmers in India
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  - Transaction-level bank account data & loan-level credit bureau data

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    - Compare $\underbrace{\text{landowning}}_{\textit{Treatment}}$ & $\underbrace{\text{non-landowning}}_{\textit{Control}}$ (*tenant*) farmers
  - Non-compliance by West Bengal
    - Falsification design
    - Border district-pair design

This Paper

Key Results

Income Multiplier = $2.7

Guaranteed Income

$1 *each year, perpetually*
PDV *@ 5.8% =* ***$17.2***

→

Income

$1.7 *additional income over the next 12 months*

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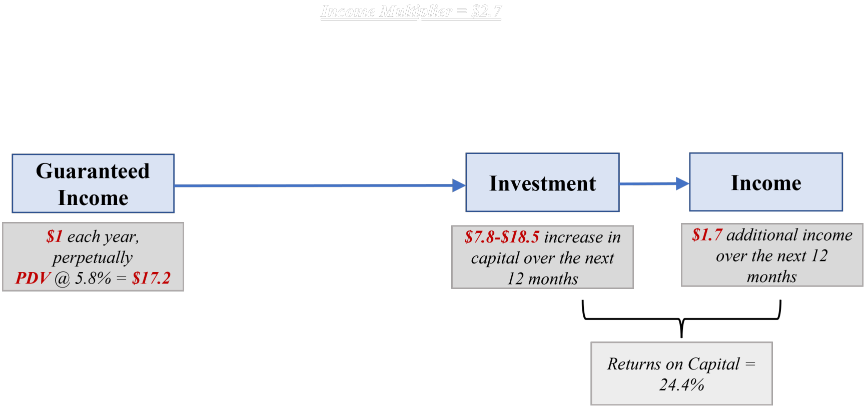
Key Results



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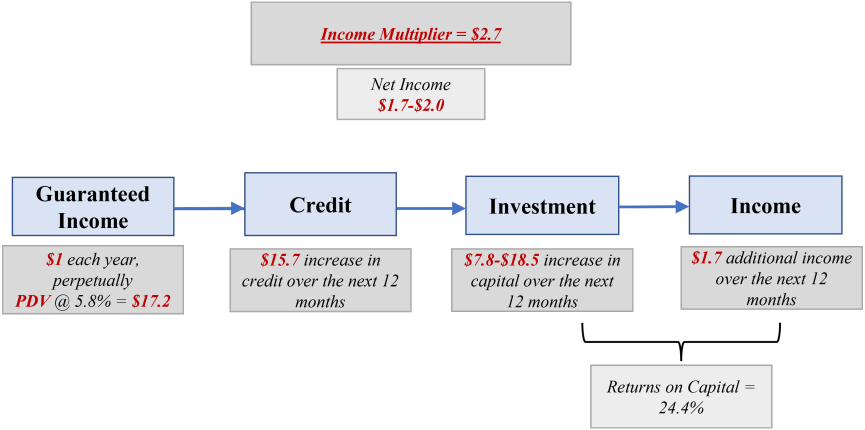

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Mechanism: Guaranteed income reduces downside risk associated with debt contracts

- What drives the credit market effect?
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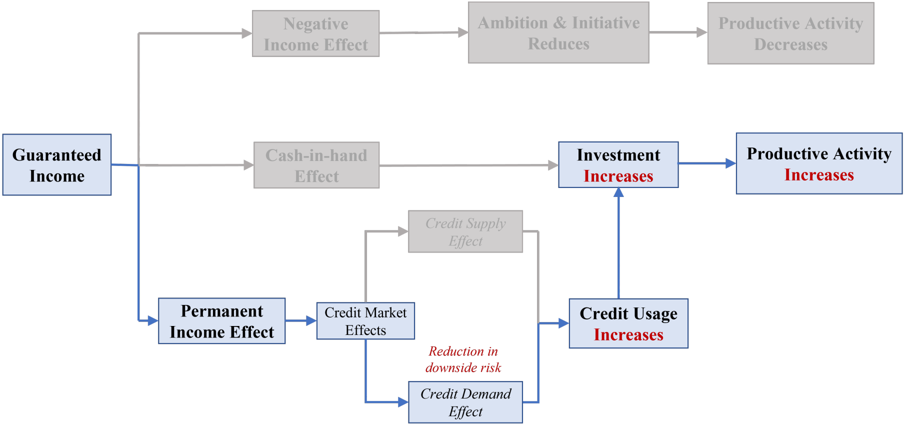
- What drives increased demand for credit?
  - Key: Debt contracts + Bad Times ⇒ Cost of Distress ▸ CFD
    - ⇒ Low Credit Demand
  - Using an original large survey of farmers we find guaranteed income:
    - Increases demand for credit by:

    1. Improving debt repayment ability & comfort
    2. Reducing (expected) permanent consumption loss due to default

This Paper

In a Nutshell



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Implications & Contribution

- **Implications:**
  1. Instead of *reducing* ambition, recipients work *differently*
     - Shift to a capital-intensive mode of production
  2. Guaranteed Income dilutes demand-side barriers that result in under-investment

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Implications & Contribution

- **Implications:**
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  2. Guaranteed Income dilutes demand-side barriers that result in under-investment

- **Contribution:**
  1. Evaluation of a large guaranteed income program
     - + novel matched data for future research
  2. What are the impediments to investment by micro-entrepreneurs?
     - Uninsured risk may play a key role
  3. Potential explanation for the Euler Equation Puzzle
     - i.e., why is loan take-up low despite improving access to credit and high returns on capital?
     - **Answer:** Uninsured risk + High risk-aversion $\Rightarrow$ $\underbrace{\text{Under investment}}_{\text{Leaving money on the table}}$

Roadmap

1. Setting, Data, & Methodology
2. Effect on Income
3. Effect on Investment
4. Effect on Credit
5. Role of Credit Demand
6. What Causes the Increase in Demand
7. Conclusion

Institutional Details

Program Flow

Prime Minister's Farmer's Tribute Fund

- Guaranteed Income (GI) or Basic Income (BI) Program
  - Pradhan Mantri Kisan Samman Nidhi (PMKSN) or Prime Minister's Farmer's Tribute Fund
    - Announced during interim-budget in February, 2019
    - Launched in March, 2019
  - Perpetual annual unconditional (no strings attached) income of ₹6,000 ($ 84) to all landowning farmers
    - Beneficiaries represent 67% of all farmers and 27% of total population
    - Disbursed in three equal installments of ₹2,000
  - Total amount of $11 billion each year, accounting for:
    - 0.51% of total GDP
    - 4% of GDP from agriculture
    - 3.5% of government consumption expenditure

How does the BI program affect farmers?

- Permanent Income Shock
  - Raises the income of landowning farmers by ₹6,000 per annum
    - $84 in nominal terms
    - $285 in PPP terms
- Liquidity Effect
  - Represents 3-6% of (annual) income for the average farmer
  - Equivalent to 1.6X farmer's average (monthly) stock of saving
- Unearned Income Effect
  - Perpetuity value of GI represents 27.2 times savings
    - $\text{PV} = \frac{6{,}000}{5.8\%} = ₹103{,}448.28$
    - Average monthly savings (stock) $=$ ₹3,803.82

Why Use this Experiment?

- Immutability: Landownership status defined as of December 2018
  - Ensures stability of treatment & control groups
- Unconditional: Orthogonal to income, wealth, or effort
  - Necessary to isolate the effects of these transfers, holding fixed other determinants
- Highly unexpected
  - Precluding the possibility of anticipatory effects
- Farmers are tax exempt
  - Allows focusing on PE forces
  - as well as the assumption of homogeneity of the treatment

Bank Data: Income, Savings, & Spending

Back

- Novel data from a large commercial (private) bank in India
  - Joint measurement of income, savings, & spending
- Tracks savings account details, long-term savings, debit and credit card transactions for every farmer over time
  - Sample of 86,873 farmers with 2.2 million farmer-by-month observations
  - Income = Inflows - Loans - Investment - PMKSN Transfers
- Information on ZIP code and landownership
  - Landowning (treatment group) and Non-Landowning (control group)
- Caveat: Can only measure banked income
  - Possibly accounts for 45-50% of farmer's income
    - Similar across treatment & control groups

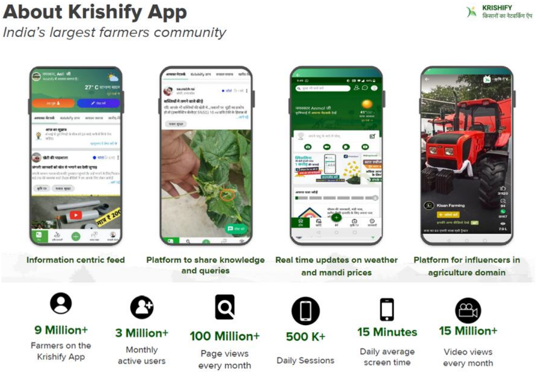
Credit Bureau Data ▸ Back

- We collect data on all loans disbursed to the farmers in our sample
  - This dataset does not include data on any type of credit cards
  - We collect this data by doing an inquiry for our sample farmers at the credit bureau (TransUnion-CIBIL)
    - ★ The data provides information on date of loan disbursal, loan amount, purpose of loan and the bank type of the disbursing loan
    - ★ The data provides the date of the inquiry for the farmers, if an inquiry was made
    - ★ We are able to collect all borrowing information for 43,619 ($\approx$ 50%) farmers in our original sample
  - Caveat: We can only observe loans from formal sources
    - ★ 60% of farmers indicate formal sources as primary source of borrowing
    - ★ Similar across treatment & control groups

About Our Survey Partner: Krishify ▸ Back

Also, known as *The Facebook of Farmers*

- Founded in 2019
- Network of 9.5mn farmers
- Limited to:
  - Hindi speakers
  - Smart-phone users



Data

- Transaction-level bank data ▸ Data
- Loan-level credit bureau data (matched with bank data) ▸ Data
- Primary data from a field survey ▸ Data
- Data on beneficiaries of PMKSN ▸ Data
- Data on entry of agri-based micro-enterprises ▸ Data
- Remote sensing data on agricultural yields ▸ Data
- CPHS household survey data by CMIE ▸ Data
- Data on market-level prices of agri-produce ▸ Data
- Other data sets ▸ Data

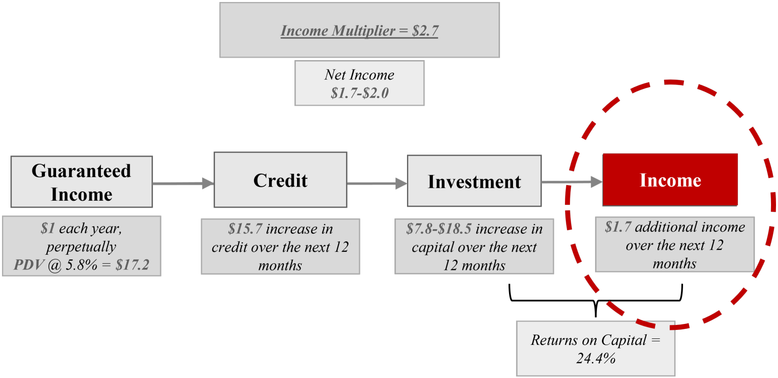
Empirical Strategy

- Compare $\underbrace{\text{landowning}}_{\textit{Treatment}}$ & $\underbrace{\text{non-landowning}}_{\textit{Control}}$ (*tenant*) farmers
  - Concern: Across group differences + local demand shocks ▸ Discussion
- Empirical Specification:

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \cdot 1(t=k) + \theta_i + \theta_{z,t} + \varepsilon_{i,z,t}$$

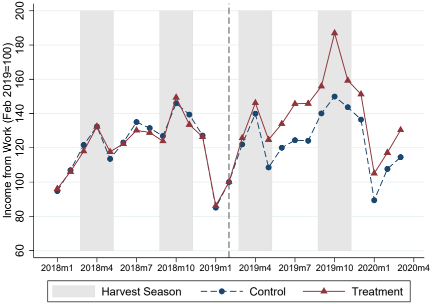
  - Farmer FE (θ_i) address time-invariant systematic differences
  - ZIP code × month FE ($\theta_{z,t}$) control for local demand shocks
  - Standard errors clustered at ZIP code level
- Key Identifying Assumptions: ▸ Discussion on Other Assumptions
  - First stage ▸ Discussion
  - Parallel trends

Effect on Income

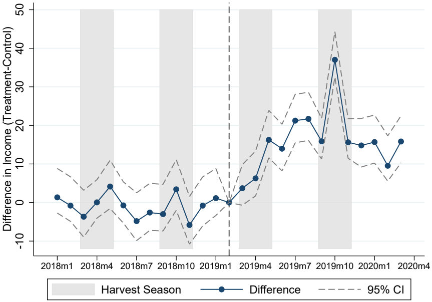


Unconditional Results

Income of treatment group increases after the policy



(a) Evolution of Income



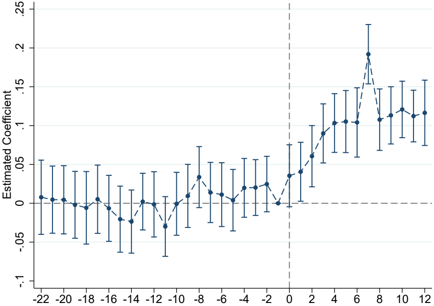
(b) Difference (Treatment-Control)

- Income from Work = Inflows - Loans - Fin Inv - Transfers
- Note: Income does not include PMKSN cash transfers

Dynamic Specification

\$1 of guaranteed income ⇒ additional \$1.7 income

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \sum_{k=-22, k\neq -1}^{k=12} \beta_k \cdot Treatment_i \cdot 1(t=k) + \underbrace{\theta_i}_{Farmer\ FE} + \underbrace{\theta_{z,t}}_{ZIP \times Month\ FE} + \varepsilon_{i,t}$$



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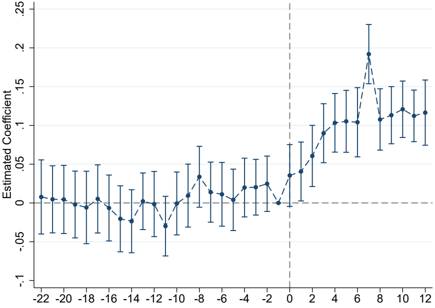
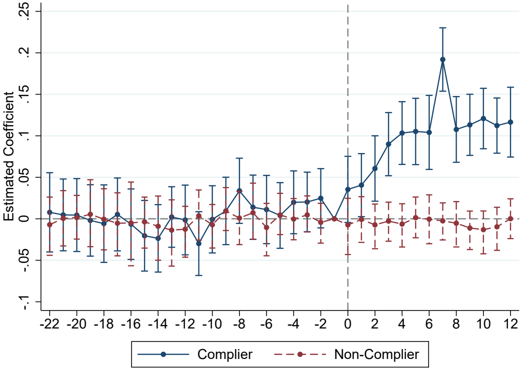


- Estimate of income multiplier $= 2.7\ (\underbrace{\boxed{1.7}}_{\text{Policy's Effect}} + \underbrace{1}_{\text{Direct Transfer}})$

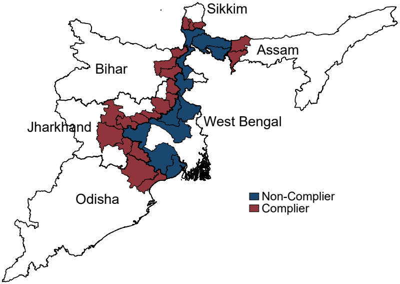
Dynamic Specification: Falsification

The state of West Bengal did not comply with the policy

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \cdot 1(t=k) + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$



Border District-Pair Design



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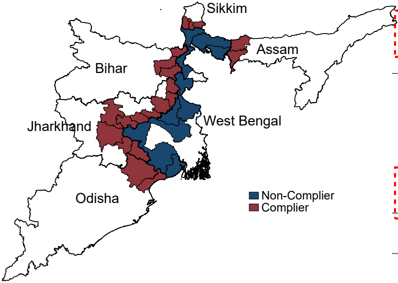


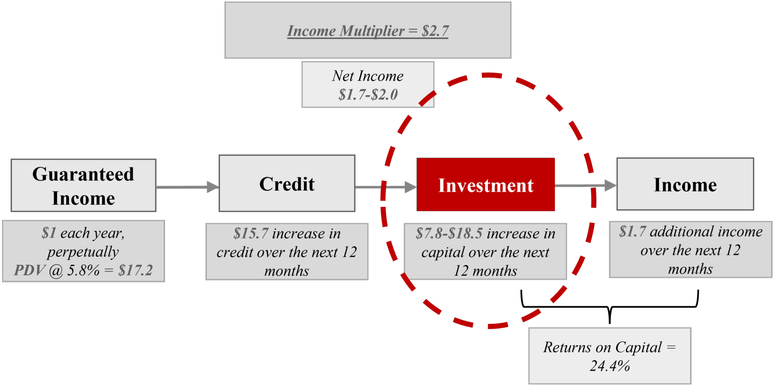
Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Treatment X Complier X Post	0.1085**	0.1084**	0.1084**	0.1306**
	(0.0494)	(0.0498)	(0.0499)	(0.0637)
Household FE	Yes	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes	Yes
Treatment X Month FE	Yes	Yes	Yes	
District-Pair X Month FE		Yes	Yes	
District-Pair X Treatment FE			Yes	
District-Pair X Treatment X Month FE				Yes
# Obs	41,253	41,253	41,253	41,253
R^2	0.6306	0.6306	0.6306	0.6334

- A district-pair is defined as the pair of two contiguous districts one in West Bengal and another in the adjoining state

Robustness

- Effect on Agricultural Productivity ▸ Results
- Placebo test – Null results in prior years ▸ Results
- Stable Unit Treatment Value Assumption (SUTVA)
  - Examining spillovers à la Berg, Reisinger and Streitz (2021) ▸ Results
- Baseline regression with covariates ▸ Results
- Alternative sample
  - Matched sample ▸ Results ▸ Sample
  - ZIP codes with single branch ▸ Results
  - Household level income from CMIE survey data ▸ Results
- Alternative transformations of the dependent variable
  - Log(1+Income) ▸ Results; Income ▸ Results; Inverse Hyperbolic Sine (IHS) Transformation ▸ Results

Effect on Investment



Effect on Investment

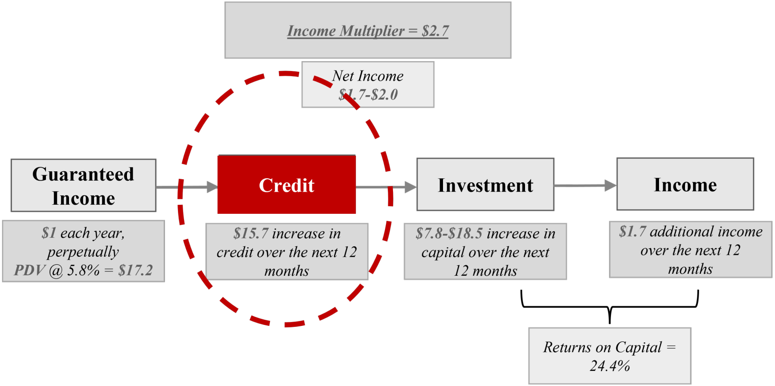
- Greater Lumpy Investment & Mechanization
  - Ownership of Tractors $\rightarrow$ 13.5% $\uparrow$ Results-1 Results-2 Results-3
  - Ownership of Livestock $\rightarrow$ 26.8% $\uparrow$ Results
  - Ownership of Two-Wheelers $\rightarrow$ 6.8% $\uparrow$ Results

- Increased Consumption of Inputs Fertilizer Irrigation
  - Fertilizer consumption:
    - ★ # of beneficiaries (1% $\uparrow$) $\Rightarrow$ (6.0% $\uparrow$) NPK consumption
  - Irrigation utilization:
    - ★ # of beneficiaries (1% $\uparrow$) $\Rightarrow$ (5.5% $\uparrow$) irrigation

The income support allows farmers to work *differently*

- \$1 of guaranteed income $\Rightarrow$ \$7.75 of additional capital (lower-bound) ▸ Results
  - Annualized returns on capital = 24.4% ▸ Magnitude
- Capital stock increases by 45% of perpetuity value (PDV) of GI @ 5.8%

Effect on Credit



Effect on Credit

- Effect on credit ▸ Results ▸ Robustness
  - Extensive Margin: Probability of new loan $\rightarrow$ 10.91 % $\uparrow$
  - Intensive Margin
    - ⋆ # New loans $\rightarrow$ 12.95 % $\uparrow$
    - ⋆ Loan amount $\rightarrow$ 16.85 % $\uparrow$
- What does the new credit finance? ▸ Results ▸ Robustness
  - Almost all new credit finances productive capacity

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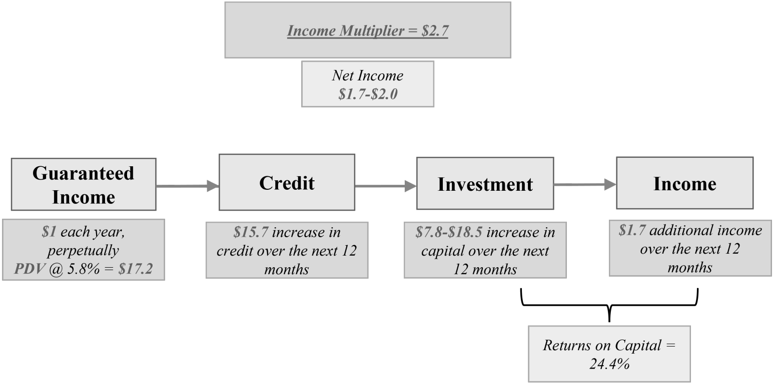
- How important are credit markets?
  - Exploit importance of credit market frictions
    - Effect absent for farmers with prior default ▸ Income ▸ Credit

Role of Credit Demand



Guaranteed Income ***increases*** **credit demand** by reducing downside risk

Existence of a Credit Demand Effect

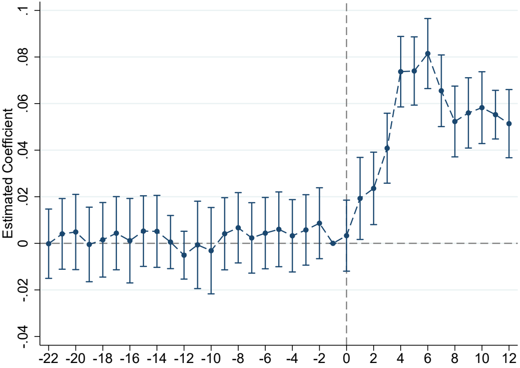
- Focus on one product – Kisan Credit Cards (KCC)
  - Hold supply constant here, w/o any assumptions
- Institutional Details
  - A widespread interpretation of RBI guidance has made this product insensitive to credit worthiness
    - RBI released an example to compute credit limit for KCCs Link
    - Example does not account for credit-worthiness
    - Banks directly follow the illustration
- Empirical Evidence – KCC credit limits and interest rates are:
  - Unrelated to credit-worthiness Results
  - Do not respond to the policy Results
- ⇒ Supply side for KCC does not respond to credit worthiness

Effect of the Policy on Utilization Rate of KCC

Table

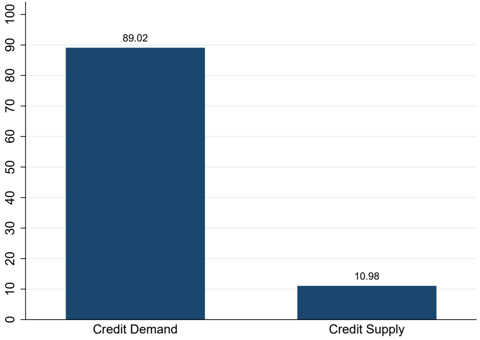
Utilization of Kisan Credit Cards Increases by 6.75 pp

$$UR_{i,t} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \cdot 1(t=k) + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$



What drives increased Borrowing?

Evidence from the Original Survey



- Question: Primarily, in what way did this (PMKSN) money increase your borrowings?
  1. It made me more comfortable to borrow (*Credit Demand*)
  2. It made the bank more willing to accept my application and/or lend me money at a low-interest rate (*Credit Supply*)

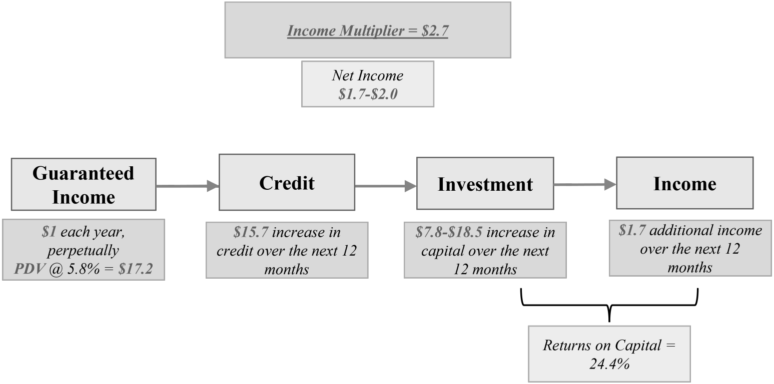
Other Suggestive Evidence on Demand Side Effect ▸ Assumption

Do not find evidence of a supply-side response

	(1)	(2)	(3)
	Inquiry (=1)	$\frac{\#Inquiry}{Avg(\#Inquiry_{Pre})}$	Accept (=1)
Treatment X Post	0.0828***	0.3646***	-0.0038
	(0.0244)	(0.1010)	(0.0195)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	
ZIP X Month FE			Yes
# Obs	87,238	87,238	79,606
R^2	0.403	0.408	0.077
Sample Mean	0.259	1.074	0.085

- $\underbrace{Pr[Loan]}_{\uparrow} = \underbrace{Pr[Application]}_{\text{Demand} = \uparrow} \times \underbrace{Pr[\frac{Accept}{Application}]}_{\text{Supply} = \text{No Effect}}$

What Causes the Increase in Demand?



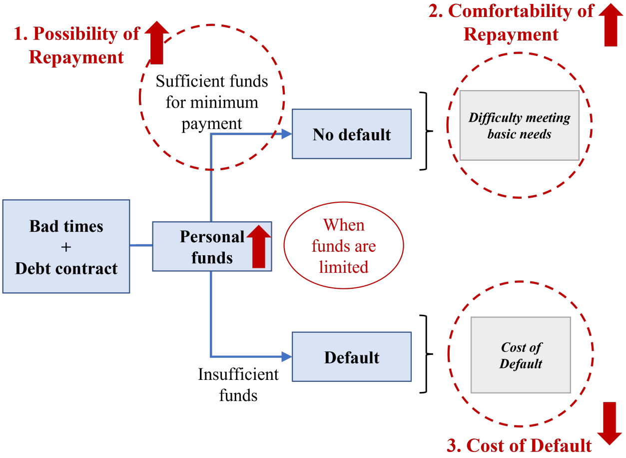
Guaranteed Income ***increases*** **credit demand** by ***reducing*** **downside risk**

What Increases Demand?

- Effect is higher when:

1. Probability of *bad* state is high ‣ Results
   - ⋆ $\Rightarrow$ Marginal benefit of guaranteed income is higher when downside risk is high
2. Insurance markets are incomplete ‣ Results
   - ⋆ $\Rightarrow$ Marginal benefit of guaranteed income is higher when the risk is uninsurable
3. Expectations of future risk protection are higher ‣ Results
   - ⋆ Announcing party vote share $\uparrow \Rightarrow$ Prob. of Continuance $\uparrow \Rightarrow$ Future risk protection $\uparrow$

How does guaranteed income increase credit demand?



How does guaranteed income increase credit demand?

Survey evidence suggests guaranteed income increases credit demand by reducing the probability and severity of financial distress in default

Mechanism	Survey Question	Percentage of Respondents
Reduced probability of default	*The money makes it possible for me to service debt during bad times*	**19.79%**
Reduced severity of default (consumption loss)	*The money does not increase my ability to service debt during bad times, but it makes me more comfortable meeting basic needs in case I default*	**38.87%**
Increased comfort in repayment during bad times	*My concern before the policy was not default but meeting basic needs after repayment during bad times, the money reduced this concern*	**22.29%**
Reduced down-payment constraint	*The money helped me meet the down-payment requirements*	**19.00%**

Conclusion

- Key Result: Guaranteed Income Programs can
  - Credit Demand $\uparrow \Rightarrow$ Investment $\uparrow \Rightarrow$ Income $\uparrow$
  - Mechanism: Protection against downside risk

- Key Takeaway
  - Biggest impediment for small enterprises $\rightarrow$ Uninsured Risk
    - Uninsured Risk + Cost of Distress $\Rightarrow$ Credit Demand $\downarrow$
  - This paper supports the *poverty as vulnerability* view of Banerjee (2004)
    - Poor entrepreneurs forgo profitable opportunities because they are vulnerable & afraid of losses
    - ... & guaranteed income programs can attenuate this problem

APPENDIX

Effect of the Policy (Taking Stock of the Magnitudes)

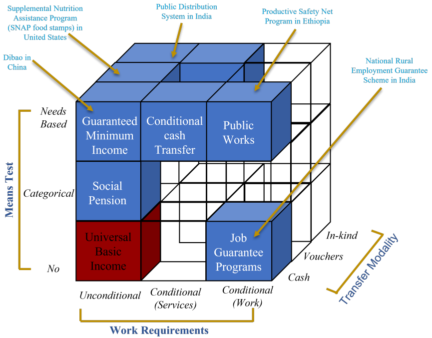
Total effect relative to $1 of guaranteed income

- Revenue
  - $\Rightarrow$ \$1.7 of additional income
- Credit
  - $\Rightarrow$ \$11.2 of additional term loans + \$4.5 of additional credit utilization
    - $\Rightarrow$ \$15.7 of additional total credit
- Capital
  - Lower Bound: \$7.75 of additional capital
  - Upper Bound: \$14-\$18.5 of additional capital (Assuming LTV = 0.8)
- Profit
  - $\Rightarrow$ \$0.70-\$0.94 of additional profits
    - Comparing ROC of 24.4% with 10^{th} (11%) and 90^{th} percentile (14.95%) borrowing rates, LTV of 0.8, and wage-to-revenue ratio of 0.14

Guaranteed Income ▸ Back

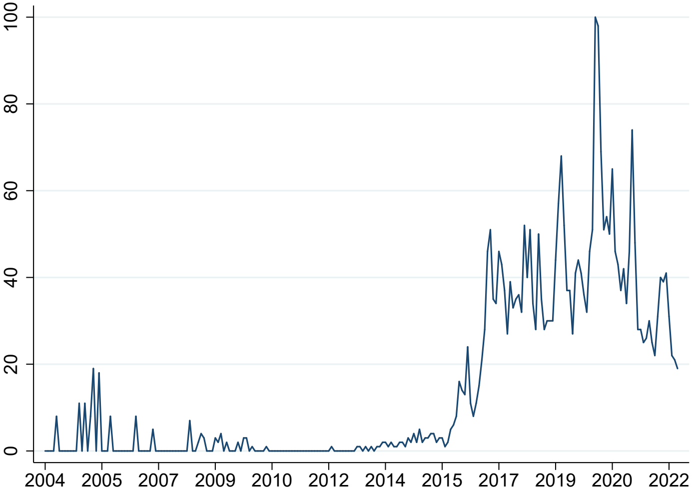
Definition: Periodic cash payment unconditionally delivered on an individual basis to all within a *well-defined community* regardless of income, wealth, employment effort, etc.

- Four key characteristics:
  1. Sufficient to live
  2. Perpetual & periodic
  3. Cash payment
  4. Unconditional
     - ★ No means test
     - ★ No work requirement



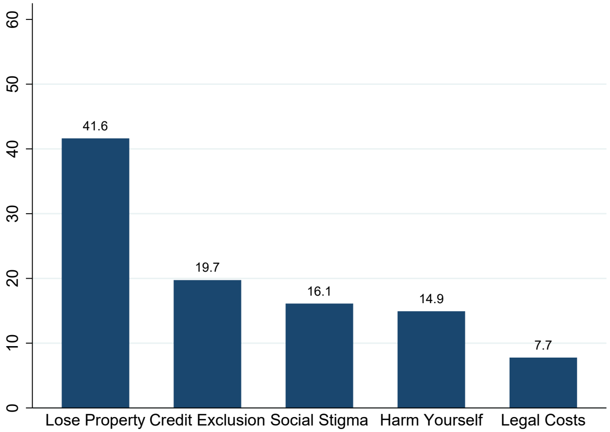
UBI Interest Over Time ▸ Back

Worldwide Google trends



Cost of Default (CFD) Back

What concerns you the most when you are unable to repay the loan?



- CFD includes future exclusion from credit markets (Garmaise and Natividad, 2017) and other economic prospects (Bos, Breza and Liberman (2018), Herkenhoff, Phillips and Cohen-Cole (2021), Cahn, Girotti and Landier (2021)) as well as social stigma (Gross and Souleles, 2002) & other fixed costs (Livshits, MacGee and Tertilt, 2010)

Examples of Cost of Financial Distress ▸ Back

REBOOT-LIVE APRIL 13, 2020 / 4:53 AM / UPDATED 2 YEARS AGO

No work, new debt: virus creates perfect storm for slavery in India

By Anuradha Nagaraj, Roli Srivastava REUTERS 6 MIN READ

CHENNAI/MUMBAI, India (Thomson Reuters Foundation) - When the coronavirus outbreak brought India to a halt last month, Bhagwan Das lost his only income as a construction worker in Delhi and embarked on a three-day trek back to his village.

Then the loan shark came knocking.

Unable to maintain repayments on the 60,000 rupee ($787) loan he took out in 2017 for his daughter's wedding, Das had no choice but to offer his son's labour to service the rising debt.

"My son works on the money lender's farmland now. He gives him food, but no wages," the 55-year-old told the Thomson Reuters Foundation by phone from central Madhya Pradesh state.

THE TIMES OF INDIA

City Chandigarh Mumbai Delhi Bengaluru Hyderabad Kolkata Chennai Agra Agartala Ahmedabad Ajmer Allahabad Amaravati

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NEWS / CITY NEWS / CHANDIGARH NEWS / Punjab: Agricultural Bank Issues Arrest Warrants For Loan Default, Farm Outfits Oppose

Punjab: Agricultural bank issues arrest warrants for loan default, farm outfits oppose

Neel Kamal & Dinesh Sharma / TNN / Updated: Apr 22, 2022, 10:09 IST

THE HINDU

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STATES ANDHRA PRADESH KARNATAKA KERALA TAMIL NADU TELANGANA OTHER STATES

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KARNATAKA

Farmers complain of banks knocking on their doors

Rishikesh Bahadur Desai

RISHIKESH BAHADUR DESAI MAY 20, 2021 19:20 IST
UPDATED: MAY 20, 2021 19:20 IST

SHARE ARTICLE PRINT A A A

They have to repay loans before May 29 or else they will be charged an annual interest at the rate of 12.5%

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OTHER STATES

Rajasthan govt. stops auction of farmers' agricultural land

Mohammed Iqbal

JAIPUR JANUARY 21, 2022 01:19 IST
UPDATED: JANUARY 21, 2022 01:20 IST

SHARE ARTICLE PRINT A A A

Toiling hard: A farmer ploughing his field in Kovia village of Udaipur district in Rajasthan.

AGRICULTURE

Ensure no coercive action taken against defaulting farmers: Supreme Court to Tamil Nadu

Petitioners argued that rise in suicide cases was due to punitive action taken by bank officials against drought-hit farmers who are not able to repay loans

Thursday, 5 May 2022

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COMMENT

Contrasting rules for farm, corporate loans

While many of the big defaulters have escaped abroad, why is it invariably a farmer (or a small borrower) who is left to face ill-treatment and injustice in the loan recovery process? While the big defaulters are treated with kid gloves, farmers are always treated with a different yardstick, as if they are children of a lesser god.

HOME / INDIA NEWS / Its Not Moneylenders 80 Farmers Commit Suicide Due To Loan From Banks

It's not moneylenders! 80% farmers commit suicide due to loan from banks

Its not moneylenders, but banks and registered micro-finance institutions that have emerged as the prime reason behind India's farmer-suicides narrative.

Written by FE Online
January 7, 2017 11:31:45 am

FINANCIAL EXPRESS Read to Lead

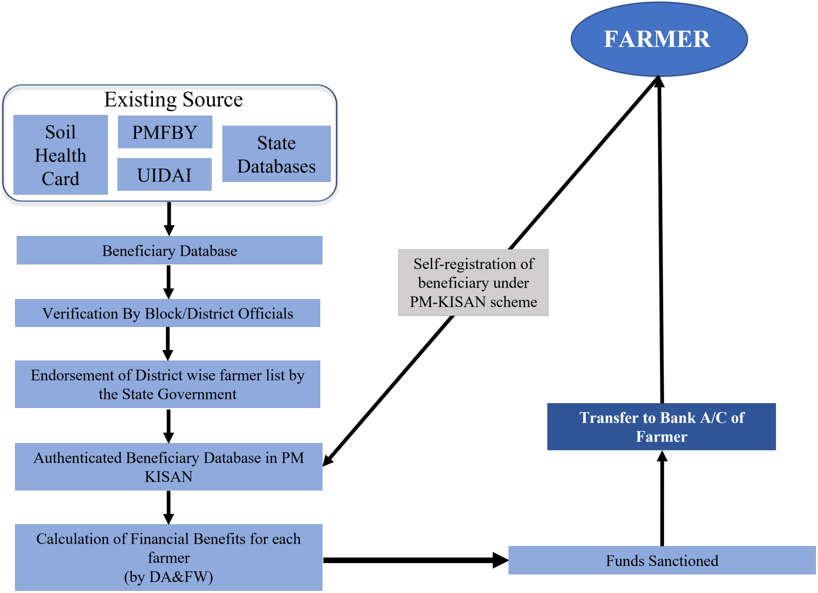
Related Literature ▸ Back

- Effect of long-term transfers
  - Imbens et al. (2001), Gertler et al (2012), Bianchi & Bobba (2013), Cesarini et al. (2017), Picchio at al (2018), Salehi-Isfahani & Mostafavi-Dehzooei (2018), Banerjee et al. (2020), Golosov et al. (2021), Jones & Marinescu (2022)
  - **Contribution 3:** evaluation of world's largest welfare program
    - ★ focus on self-employed & investment

- Role of risk-tolerance & downside risk protection in entrepreneurship
  - Knight (1921), Kihlstrom & Laffont (1979), Miller (1984), Iyigun & Owen(1998), Levesque & Minniti (2006), Olds (2016), Hombert et al. (2020), Gottlieb et al. (2021), Fazio et al. (2021)
  - **Contribution 4:** guaranteed income + developing country + demand
    - ★ esp important as insurance-based approaches have proven to be ineffective in developing markets (Cole & Xiong, 2017)
    - ★ focus on subsistence/livelihood-sustaining enterprises

Transfer Process

▸ Back



Bank Data: Income, Savings, & Spending ▸ Back

- Novel data from a large commercial (private) bank in India
  - Joint measurement of income, savings, & spending

- Contains data on all farmers across five states that have a relationship with the bank
  - States – Maharashtra, Karnataka, Punjab, Telangana, West Bengal
  - Time-period – 2017-2021 ▸ Comparison

- Tracks savings account details, long-term savings, debit and credit card transactions for every farmer over time
  - Sample of 86,873 farmers with 2.2 million farmer-by-month observations
  - Income = Inflows - Loans - Investment - PMKSN Transfers

- Information on ZIP code and landownership
  - Landowning (treatment group) and Non-Landowning (control group)

Comparison of Sample Data with National Data

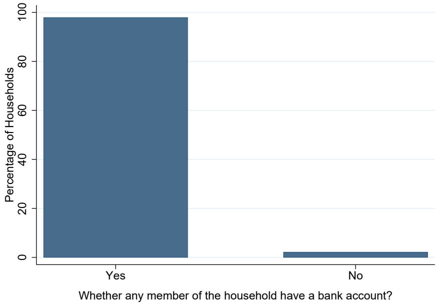
▸ Back

	Bank Data	SAS Survey Data						
		Total	Farm	Animals	Sales	Non-farm	Pension	Rent
Income (in ₹)	8,334.00	15,330.98	7,996.89	2,467.78	1,799.61	2,414.92	1,308.66	53.37
Expenditure (in ₹)	11,578.78	11,858.00						
Age (in years)	45.23	48.91						
% with outstanding credit	–	40.3%						
% with some credit history	50.2%	–						

- Bank sample data captures approximately 54.4% of farmer's income
- Our sample farmers (may) have better access to credit

Do Farmers in Rural India Have Bank Accounts?

- 98% of rural households have at least one bank account today, due to
  - The 2014 financial inclusion policy
    - *Pradhan Mantri Jan Dhan Yojana* (PMJDY)
  - The 2016 demonetization episode



2018 SAS Survey of Farmers

How Many Bank Accounts Do Farmers Have?

Number of Bank Accounts	Overall	PMKSN Recipients	PMKSN Non-Recipients
1	0.50	0.46	0.55
2	0.26	0.27	0.23
3	0.11	0.12	0.10
More than 3	0.13	0.14	0.12

- We are likely to underestimate income & spending

What Do the Inflows Really Measure? ▸ Back

Credit Bureau Data

Back

- We collect data on all loans disbursed to the farmers in our sample
  - This dataset does not include data on any type of credit cards
  - We collect this data by doing an inquiry for our sample farmers at the credit bureau (TransUnion-CIBIL)
    - The data provides information on date of loan disbursal, loan amount, purpose of loan and the bank type of the disbursing loan
    - The data provides the date of the inquiry for the farmers, if an inquiry was made
    - We are able to collect all borrowing information for 43,619 ($\approx$ 50%) farmers in our original sample

Sources of Debt ▸ Back

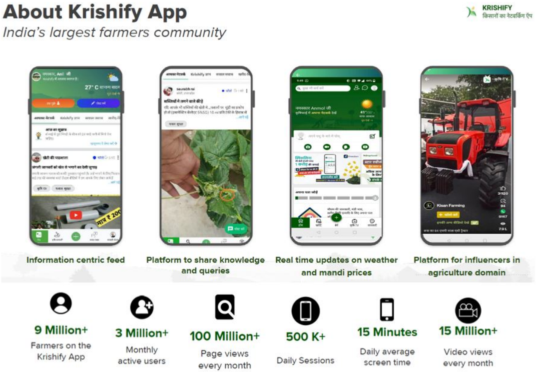
Biggest Source of Credit	Overall	PMKSN	
		Recipients	Non-Recipients
Formal Sector (Bank)	0.60	0.66	0.52
Friends and family	0.22	0.18	0.28
Moneylender	0.18	0.16	0.20

- Caveat: Our credit bureau data can only account for credit from formal sources – *banks* & other financial corporations

About Our Survey Partner: Krishify ▸ Back

Also, known as *The Facebook of Farmers*

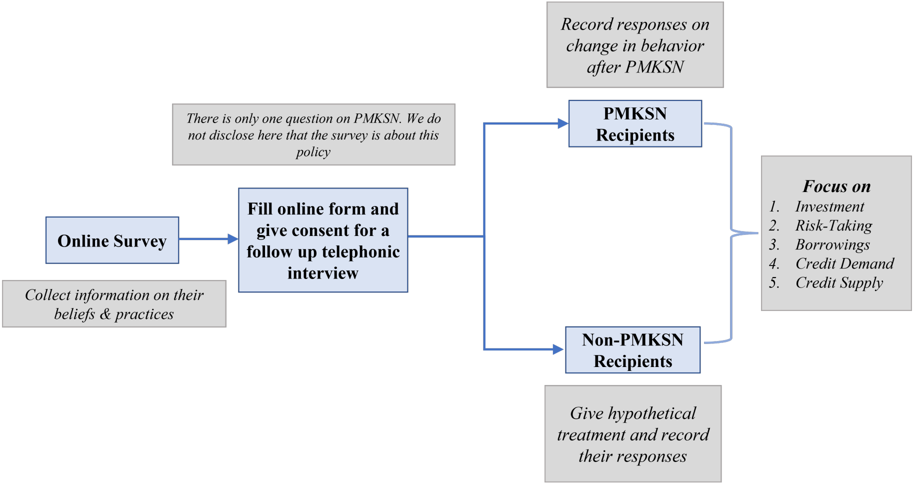
- Founded in 2019
- Network of 9.5mn farmers
- Limited to:
  - Hindi speakers
  - Smart-phone users



Primary Data from Field Survey

Back

We conduct a field survey of farmers in collaboration with Krishify

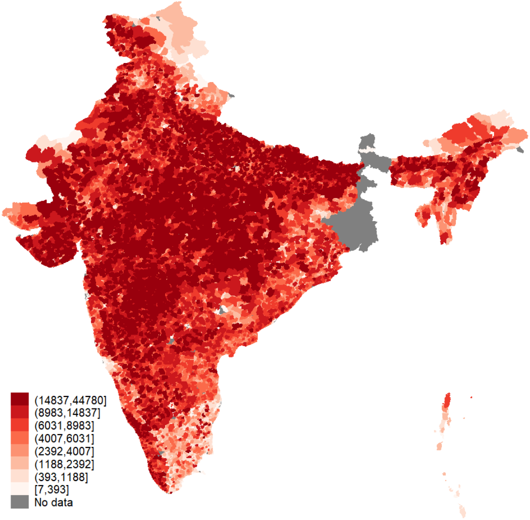


Data: Beneficiaries of PMKSNY by ZIP Code

Back

Geography of UBI benefits

- New Data
- Source: *Ministry of Agriculture, GOI*
- Universe of all beneficiaries
  - Accounts for 100% of beneficiaries of PMKSNY
- Geo-referenced using village names

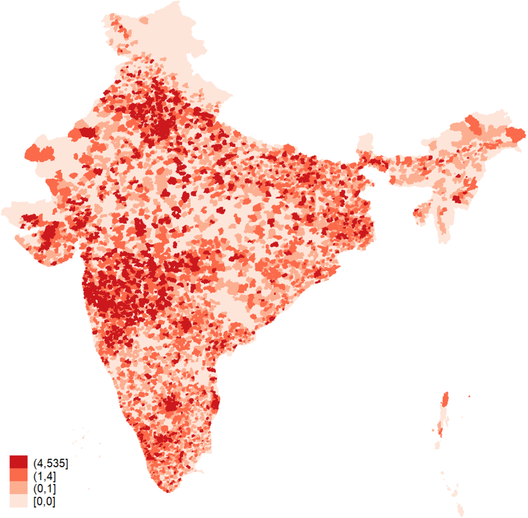


Data: Firm Entry between 2017-2019 by ZIP Code

Back

Geography of firm entry

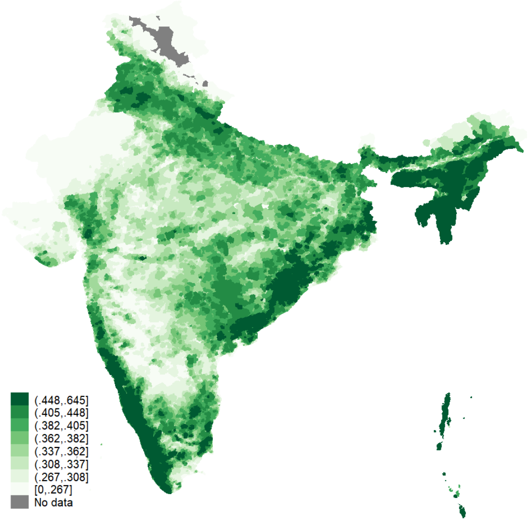
- Source: *Ministry of Corporate Affairs, GOI*
- Universe of all new firms
  - Private for-profit firms
  - Registered b/w 2017-2019
  - 55,716 firms
- Geo-referenced using address text
- Extended version of data used in Dutta, Ghosh, Sarkar & Vats (2022)



Data: Enhanced Vegetation Index, 2017-2020 ▸ Back

Geography of crop production

- Source: *Images form Landsat 8 satellite*
- Collapse the pixel level images at ZIP code level
- Extended version of data used in Asher & Novosad (2020)
- Yield is generated by subtracting the early cropping season value from the maximum growing season value



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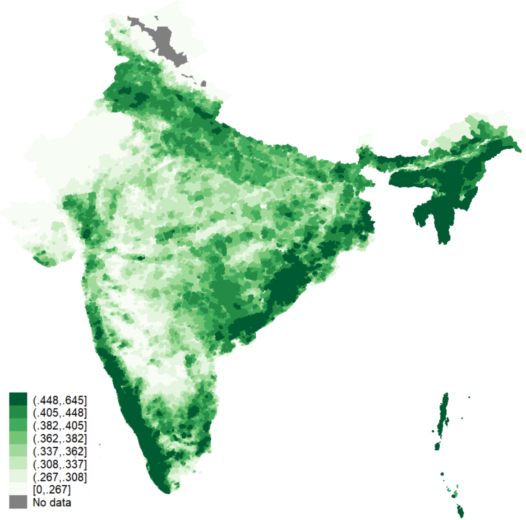


Data: Household survey ▸ Back

- Source: Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE)
  - A large panel of sample households surveyed repeatedly over time
    - ★ The survey is conducted every month
    - ★ Each household is re-surveyed every quarter
  - The survey provides data on:
    - ★ Income of households
    - ★ Expectations of financial conditions in future
    - ★ Time spent by members of households on work and leisure
    - ★ Purchased on cattle and tractors

Data: Prices of Agricultural Commodities

Back

- New data
- Source: AgMARKNET database, GOI

- This data provides information on prices of agricultural commodities across all wholesale agricultural markets (mandi) in India
- Commodities include:
  - Perishable: tomato, potato, and onions
  - Non-perishable: lentils (split pulses), millets, rice, soybean, and wheat

Other Data Sets Back

- Rainfall data
  - Source: Climate Data Service Portal
- Bank branch location
  - Source: Reserve Bank of India
- GIS files for ZIP codes
  - Source: Indian Postal Services
- Gross sown area by crops
  - Source: Ministry of Agriculture, GOI

Agriculture Value Added by States in 2019 ▸ Back

State	VA	Share	State	VA	Share
Mizoram	20,459	0.10%	Telangana	569,576	2.84%
Goa	21,370	0.11%	Odisha	606,107	3.02%
Sikkim	28,104	0.14%	Haryana	710,585	3.54%
Meghalaya	29,186	0.15%	Bihar	755,245	3.77%
Arunachal Pradesh	34,809	0.17%	Punjab	931,631	4.65%
Manipur	49,536	0.25%	Tamil Nadu	1,009,597	5.04%
Nagaland	52,359	0.26%	Andhra Pradesh	1,186,151	5.92%
Tripura	102,994	0.51%	Karnataka	1,247,413	6.22%
Himachal Pradesh	119,443	0.60%	Gujarat	1,259,540	6.28%
Uttarakhand	121,593	0.61%	Rajasthan	1,317,659	6.57%
Jharkhand	321,077	1.60%	West Bengal	1,608,448	8.02%
Kerala	364,868	1.82%	Maharashtra	1,722,922	8.59%
Assam	423,685	2.11%	Madhya Pradesh	2,294,902	11.45%
Chhattisgarh	457,547	2.28%	Uttar Pradesh	2,684,641	13.39%

Summary Statistics (Pre-policy monthly average in ₹) ▸ Back

Systematic differences across treatment & control group

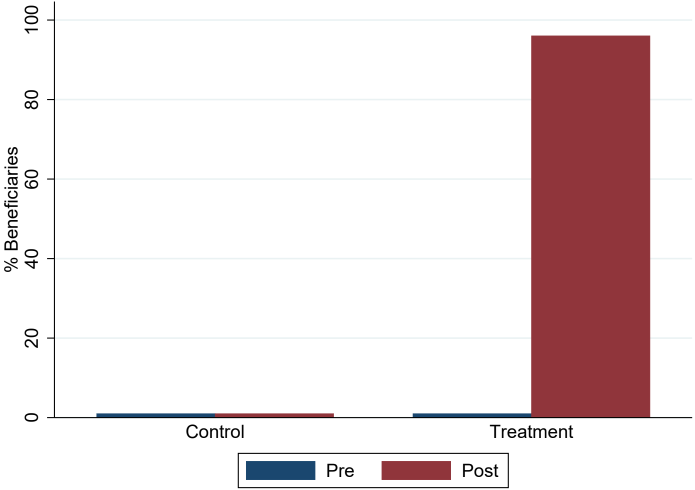
	Sample Average	Group-wise Average		Difference (T-C) *unconditional*		Difference (T-C) *within ZIP code*	
		Control (C)	Treatment (T)	Magnitude	t-stat	Magnitude	t-stat
Income	8,334.24	9,665.96	8,271.60	-1394.36***	3.23	-752.91	1.47
Savings	3,803.82	6,011.95	3,699.26	-2,312.69***	10.36	-569.37**	2.35
Expenditure	11,578.78	13,489.92	11,488.25	-2,001.67***	2.90	-1,348.14	1.54
Credit Score	524.90	526.96	524.80	-2.16	0.50	0.51	0.11
Interest Rate	11.08	10.55	11.10	0.55***	7.90	-0.18***	4.73
Frac. Default	0.297	0.300	0.297	-0.003	0.21	0.035***	2.88
KCC Credit Limit	496,862.30	424,171.40	500,241.80	76,070.41***	4.97	-19,054.52	1.01
Frac. CC User	0.007	0.015	0.007	-0.008***	3.71	-0.002	0.69
Frac. Oth Inv	0.004	0.016	0.003	-0.013***	4.27	-0.004*	1.66
Account Age	5.31	5.83	5.29	-0.54***	6.50	-1.94***	29.35
# Trnx per day	0.022	0.029	0.021	-0.008***	6.20	-0.006***	3.44
Farmer Age	45.23	44.07	45.29	1.22***	4.59	-0.43	1.28
Frac. Female	0.056	0.027	0.058	0.031***	9.63	0.015***	2.64

Other Identifying Assumptions ▸ Back

- **Homogeneity in the intensity of treatment**
  - After accounting for income taxes, the effective transfers are not identical across the income distribution
  - **Solution:** Farmers in India are tax-exempt
    - ★ Also, helps address issues related to *Ricardian Equivalence*
- **Stability of the treatment and control group**
  - Buying & selling of agricultural land can allow individuals to select in or out of the treatment group
  - **Solution:** Policy design makes landownership status an immutable characteristic, based on status in December 2018

First Stage ▸ Back

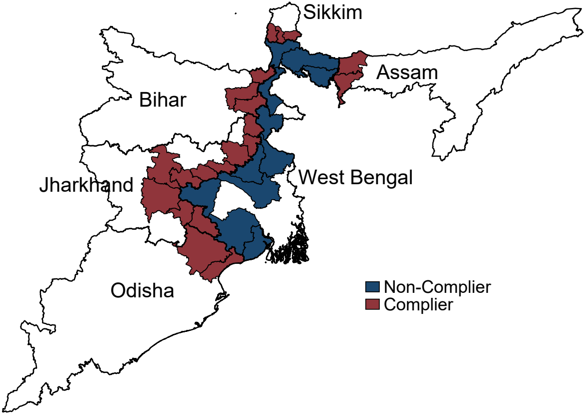
96.03% of treated farmers received the PMKSN transfers



Border Discontinuity Design

Back

Sample of bordering districts



- A district-pair is defined as the pair of two bordering districts one in West Bengal and another in the adjoining state

Border Discontinuity Design
Back

Results

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Treatment X Complier X Post	0.1085**	0.1084**	0.1084**	0.1306**
	(0.0494)	(0.0498)	(0.0499)	(0.0637)
Household FE	Yes	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes	Yes
Treatment X Month FE	Yes	Yes	Yes	
District-Pair X Month FE		Yes	Yes	
District-Pair X Treatment FE			Yes	
District-Pair X Treatment X Month FE				Yes
# Obs	41,253	41,253	41,253	41,253
R^2	0.6306	0.6306	0.6306	0.6334

Effect on Income: Farmer-by-month Level Analysis

Income of treated farmers increases by 12.6%

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \beta\, Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

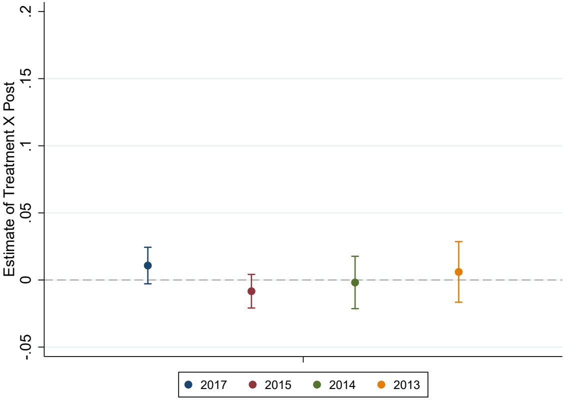
Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.0928***	0.0947***	0.1088***	0.1229***	0.1261***
	(0.0313)	(0.0311)	(0.0241)	(0.0469)	(0.0119)
Treatment	-0.1673***	-0.1670***	-0.0286		
	(0.0223)	(0.0218)	(0.0200)		
Post	-0.0012				
	(0.0303)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0002	0.0035	0.0605	0.2483	0.2705
Economic Effect (in ₹)	9,276	9,468	10,884	12,228	12,612
Economic Effect ($1 UBI)	$1.55	$1.58	$1.81	$2.05	$2.10

Robustness: Placebo Test

Back

No effect observed in previous years

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \beta \cdot Treatment_i \cdot Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,z,t}$$



Robustness: Spillovers and the Treatment Effect ▸ Back

$$\frac{y_{i,Post} - y_{i,Pre}}{y_{i,Pre}} = \beta \cdot Treatment_i + \beta_T \cdot Treatment_i \times Frac.Treated_d$$
$$+ \beta_C \cdot (1 - Treatment_i) \times Frac.Treated_d + \theta_s + \varepsilon_i$$

Dep Var: Income Growth	(1)	(2)	(3)
Treatment	0.1044***	0.1057***	0.1255**
	(0.0244)	(0.0261)	(0.0635)
Frac. Treated		-0.0078**	
		(0.0031)	
Treatment X Frac. Treated			-0.0075***
			(0.0016)
(1-Treatment) X Frac. Treated			-0.0224***
			(0.0057)
State FE	Yes	Yes	Yes
# Obs	86,873	86,873	86,873
R^2	0.0185	0.019	0.0191

Robustness: Baseline Regression with Covariates ▸ Back

The baseline estimate remains stable despite adding an array of covariates (X^j)

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \beta \cdot Treatment_i \cdot Post_t + \sum_j \gamma_j \cdot X_i^j \cdot Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,z,t}$$

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treatment X Post	0.1261***	0.1263***	0.1235***	0.1271***	0.1214***	0.1373***	0.1251***	0.1251***	0.1153***	0.1089***	0.1109***	0.1247***	0.1242***	0.1404***	0.1298***
	(0.0119)	(0.0208)	(0.0208)	(0.0204)	(0.0206)	(0.0199)	(0.0207)	(0.0207)	(0.0204)	(0.0193)	(0.0204)	(0.0207)	(0.0207)	(0.0204)	(0.0189)
Age X Post		-0.2124***													-0.3876***
		(0.0270)													(0.0260)
KCC Limit X Post			0.0050***												0.0236***
			(0.0013)												(0.0014)
Default X Post				-0.3065***											-0.3118***
				(0.0145)											(0.0174)
Int Rate X Post					0.0088*										-0.0154***
					(0.0046)										(0.0046)
Relationship X Post						0.3491***									0.3259***
						(0.0333)									(0.0370)
CC User X Post							0.3379***								1.0222***
							(0.1161)								(0.1246)
Other Inv X Post								0.2022							0.3082*
								(0.1691)							(0.1670)
Liquid Wealth X Post									-0.0183***						0.0087***
									(0.0013)						(0.0015)
Consumption X Post										-0.0390***					-0.0444***
										(0.0014)					(0.0016)
% Visits X Post											-0.0356***				-0.0287***
											(0.0020)				(0.0023)
Credit Score X Post												0.0911***			0.0901***
												(0.0044)			(0.0049)
Female X Post													-0.0123		-0.0352
													(0.0234)		(0.0227)
Hindu X Post														-0.1426***	-0.0068
														(0.0159)	(0.0170)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP X Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,142,572	2,169,451	2,169,451	2,169,451	2,169,451	2,142,572
R^2	0.434	0.4341	0.434	0.4344	0.434	0.4342	0.434	0.434	0.4342	0.4316	0.4346	0.4344	0.434	0.4341	0.4331

Robustness: Matched Sample Regression ▸ Back

Addresses issue of systematic differences between landed & non-landed farmers

$$\frac{y_{i,t}}{Avg(y)_{Pre}} = \beta\, \mathit{Treatment}_i \times \mathit{Post}_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)
Treat X Post	0.1160**	0.1107**
	(0.0530)	(0.0531)
Farmer FE	Yes	Yes
ZIP Code X Month FE	Yes	
Matched Pair X Month FE		Yes
# Obs	42,052	42,052
R^2	0.6036	0.8347

Summary Statistics for Matched Sample

Back

Systematic differences across treatment & control group

	Overall	Sample		Difference	
		Control	Treatment	Magnitude	t-stat
Income from Work	12,925.51	12,448.91	13,402.11	-953.20	1.63
Savings	8,243.09	8,759.10	7,994.84	764.26	1.02
Consumption	7,420.02	7,382.83	7,457.93	-75.11	0.24
Frac. CC User	0.019	0.019	0.018	0.001	0.09
# Trnx per day	0.048	0.045	0.049	-0.005	0.96
Credit Score	561.63	553.03	565.78	-12.76	1.36
Interest Rate	9.19	9.11	9.22	-0.11	0.97
Frac. Default	0.210	0.219	0.205	0.014	0.58
Farmer Age	44.33	44.21	44.39	-0.18	0.24
Account Age	6.40	6.49	6.36	0.13	1.27
Frac. Female	0.048	0.029	0.057	-0.029**	2.26
Frac. Other Investment	0.010	0.019	0.006	0.013**	2.25
Sanction Limit	397,161.20	344,278.40	422,603.10	78,324.7**	2.26

Robustness: ZIP Codes with Single Branch ▸ Back

Addresses the concern the selection into the sample bank

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.1043***	0.1066***	0.0815**	0.1712***	0.1398***
	(0.0390)	(0.0388)	(0.0102)	(0.0514)	(0.0118)
Treat	-0.1691***	-0.1693***	-0.0518		
	(0.0182)	(0.0179)	(0.0220)		
Post	-0.0214				
	(0.0375)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	161,272	161,272	161,272	161,272	161,272
R^2	0.0003	0.0038	0.0775	0.2395	0.2718

Robustness: Using CPHS Data ▸ Back

Income from work increases by 10.98%

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.1103***	0.1043***	0.1104***	0.1087***	0.1098***
	(0.0239)	(0.0240)	(0.0238)	(0.0238)	(0.0238)
Household FE	Yes	Yes	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes	Yes	Yes
Education group X District FE		Yes	Yes	Yes	Yes
Education group X Month FE		Yes	Yes	Yes	Yes
Gender group X District FE			Yes	Yes	Yes
Gender group X Month FE			Yes	Yes	Yes
Age group X District FE				Yes	Yes
Age group X Month FE				Yes	Yes
HH Size group X District FE					Yes
HH Size group X Month FE					Yes
# Obs	466,600	466,600	466,600	466,600	466,600
R^2	0.6677	0.6746	0.6793	0.6841	0.6894
Sample Mean	8,278.44	8,278.44	8,278.44	8,278.44	8,278.44

Robustness: Alternative Transformation ▸ Back

LN(1+y) transformation of income indicates an increase of 11.6% in income

Dep Var: LN(1+Income)	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.0964***	0.0979***	0.0932***	0.1213***	0.1158***
	(0.0192)	(0.0193)	(0.0197)	(0.0188)	(0.0194)
Treat	-0.1374***	-0.1373***	-0.0450**		
	(0.0165)	(0.0165)	(0.0178)		
Post	-0.0359				
	(0.0369)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0012	0.0165	0.0915	0.4128	0.4327

Robustness: Alternative Transformation ▸ Back

Level transformation of income indicates an increase in income by ₹840.45, 10.08% over the mean

Dep Var: Income	(1)	(2)	(3)	(4)	(5)
Treat X Post	773.42**	789.07**	681.57*	1024.58***	840.45**
	(382.82)	(385.47)	(386.24)	(390.93)	(402.40)
Treat	-1394.37***	-1391.62***	-831.92**		
	(380.92)	(382.56)	(413.08)		
Post	-10.14				
	(368.76)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0002	0.0035	0.0381	0.2483	0.2705

Robustness: Alternative Transformation ▸ Back

IHS transformation indicates the income of treated farmers increases by 12.4%

Dep Var: $LN(y+\sqrt{(1+y^2)})$	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.1034***	0.1050***	0.1000***	0.1298***	0.1240***
	(0.0206)	(0.0207)	(0.0210)	(0.0200)	(0.0207)
Treat	-0.1480***	-0.1479***	-0.0476**		
	(0.0177)	(0.0177)	(0.0191)		
Post	-0.0392				
	(0.0394)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0012	0.0165	0.0915	0.4143	0.4340

Effect on Agricultural Yield ▸ Back

10% increase in number of beneficiaries increases agricultural productivity by 8.1%

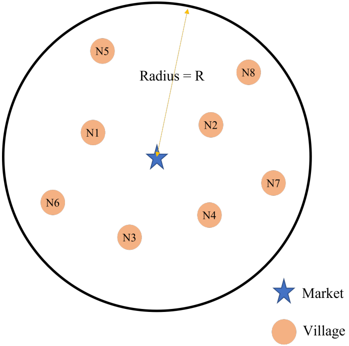
$$LN(Y_{z,s,t}) = \beta \cdot LN(\#Beneficiaries_z) \cdot Post_t + \theta_{z,s} + \theta_{s,t} + \varepsilon_{z,s,t}$$

Dep Var: LN(Yield)	(1)	(2)	(3)	(4)	(5)
LN(#Beneficiaries) X Post	0.0785***	0.0787***	0.0787***	0.0810***	0.0808***
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0078)
LN(#Beneficiaries)	0.0139***	0.0140***	0.0140***		
	(0.0003)	(0.0003)	(0.0003)		
Post	0.0069***	-0.0126***			
	(0.0018)	(0.0018)			
Season FE		Yes			
Season X Year FE			Yes	Yes	Yes
ZIP Code FE				Yes	
ZIP Code X Season FE					Yes
# Obs	114,614	114,614	114,614	114,614	114,614
R^2	0.042	0.3986	0.404	0.7199	0.8845
Sample Mean (Y Variable)	0.168	0.168	0.168	0.168	0.168
St Dev (Y Variable)	0.156	0.156	0.156	0.156	0.156
Sample Mean (X Variable)	4,766	4,766	4,766	4,766	4,766
St Dev (X Variable)	6,701	6,701	6,701	6,701	6,701

Effect on Prices of Agricultural Commodities ▸ Back

Data Construction: Mapping beneficiaries to agricultural wholesale markets

- Draw circle of radius R_m around the wholesale market
- Geo code villages
- Assign all beneficiaries within the circle to the market



Effect on Prices of Agricultural Commodities ▸ Back

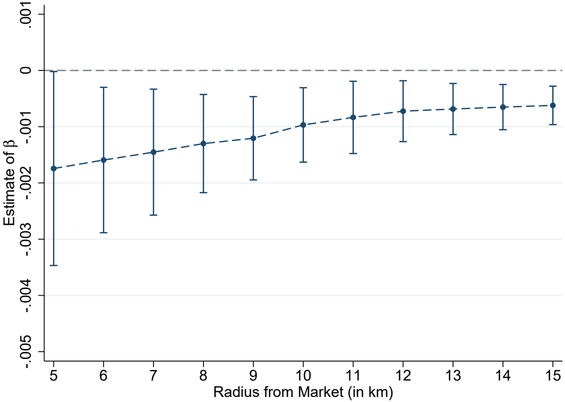
$$LN(P_{c,m,t}) = \beta \cdot Perishable_c \cdot LN\{\sum_{v \in R_m} b_v\} \cdot Post_t + \gamma LN(P_{c,m,t-1}) + \theta_{m,t} + \theta_{c,t} + \theta_{c,m} + \varepsilon_{c,m,t}$$

- $LN(P_{c,m,t})$ denotes log prices of commodity (c), in wholesale market (m) during month (t)
- b_v denotes the total number of beneficiaries in village v
- R_m denotes the radius around market m
- Assumption: Perishable commodities are more likely to be locally sourced
  - Perishable commodities include tomatoes, potatoes, and onions

Effect on Prices ▸ Back

Prices of perishable agricultural goods decline after the policy: Increasing beneficiaries by 10% reduces prices of perishable commodities by 0.10%

$$LN(P_{c,m,t}) = \beta \cdot Perishable_c \cdot LN\{\sum_{v \in R_m} b_v\} \cdot Post_t + \gamma LN(P_{c,m,t-1}) + \theta_{m,t} + \theta_{c,t} + \theta_{c,m} + \varepsilon_{c,m,t}$$



Increased Capital Investment Among Farmers ▸ Back

Treatment households report buying more tractors, livestock and two-wheelers

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1) Tractors	(2) Cattle	(3) Two-Wheelers
Treatment X Post	0.1350***	0.2679***	0.0677***
	(0.0335)	(0.0352)	(0.0109)
Household FE	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes
Education group X District FE	Yes	Yes	Yes
Education group X Month FE	Yes	Yes	Yes
Gender group X District FE	Yes	Yes	Yes
Gender group X Month FE	Yes	Yes	Yes
Age group X District FE	Yes	Yes	Yes
Age group X Month FE	Yes	Yes	Yes
HH Size group X District FE	Yes	Yes	Yes
HH Size group X Month FE	Yes	Yes	Yes
# Obs	170,163	170,163	170,163
R^2	0.8124	0.5594	0.7933
Sample Mean	0.0900	1.6155	0.7195

Effect on Tractor Sales Back

Sales of tractors for agricultural purposes increases – Vahan (Ministry of Road Transport)

Dep Var: $\frac{y_{z,t,a}}{Avg(y_{Pre_a})}$	(1) Number	(2) Amount
Agricultural Purpose X Post	0.1732***	0.1763***
	(0.0252)	(0.0320)
Zipcode X Month FE	Yes	Yes
Agricultural Purpose X Zipcode FE	Yes	Yes
# Obs	347,468	347,468
R^2	0.8157	0.6569
Sample Mean	3.021	1,863,074

Effect on Tractor Sales

Back

Treatment states report higher sales of tractors – Tractor Junction data

Dep Var: Tractor Sales	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.3514**	0.3515**	0.3513**	0.3433**	0.3495**	0.3525**
	(0.1625)	(0.1626)	(0.1627)	(0.1619)	(0.1475)	(0.1463)
Treat	0.1697	0.1689				
	(0.3459)	(0.3457)				
Post	-0.0879					
	(0.1585)					
Month FE		Yes	Yes	Yes		
State FE			Yes			
State X Model FE				Yes	Yes	
State X Make FE				Yes	Yes	
Month X Model FE					Yes	
Month X Make FE					Yes	
Month X Model X Make FE						Yes
State X Model X Make FE						Yes
# Obs	23,439	23,439	23,439	23,439	23,439	23,439
Pseudo R^2	0.0076	0.0338	0.1759	0.8392	0.8492	0.9095
Sample Mean	63.9756	63.9756	63.9756	63.9756	63.9756	63.9756

Effect on Fertilizer Consumption ▸ Back

1% increase number of beneficiaries increases fertilizer consumption by 6%

Dep Var: $\frac{y_{i,s,t}}{Avg(y_{Pre})}$	(1)	(2)	(3)	(4)
	Total	Nitrogen	Phosphorus	Potassium
LN(Beneficiaries) X Post	0.0598***	0.0543***	0.1016***	0.0274
	(0.0210)	(0.0191)	(0.0297)	(0.0367)
District X Season FE	Yes	Yes	Yes	Yes
State X Season X Year FE	Yes	Yes	Yes	Yes
# Obs	3,995	3,995	3,995	3,995
R^2	0.9344	0.9241	0.9146	0.8339
Sample Mean (in tonnes)	17,500	11,100	4,207	985

Effect on Irrigation ▸ Back

1% increase number of beneficiaries increases fertilizer consumption by 5.5%

Dep Var: $\frac{y_{i,t}}{Avg(y_{Pre})}$	(1) All Sources	(2) Government Sources	(3) Private Sources
LN(Beneficiaries) X Post	0.0549**	0.0347	0.0618**
	(0.0230)	(0.0270)	(0.0271)
District FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
# Obs	1,296	1,296	1,296
R^2	0.9881	0.9868	0.9873
Sample Mean (in '000 tonnes)	112.50	27.42	85.08

Effect on Entry of Micro-Enterprises

Back

1% increase number of beneficiaries increases entry of new agri-based micro-enterprises by 5.3%

Dep Var: # New Firms	(1)	(2)	(3)	(4)
LN(# Beneficiaries) X Post	0.0570***	0.0601***	0.0458***	0.0527***
	(0.0138)	(0.0138)	(0.0131)	(0.0131)
LN(# Beneficiaries)	0.0735***	0.0699***		
	(0.0129)	(0.0129)		
Post	-0.1242			
	(0.1124)			
Month FE		Yes	Yes	Yes
ZIP Code FE			Yes	Yes
Avg(# New Firms$_{Pre}$) X Post				Yes
# Obs	34,658	34,658	34,658	34,658
Pseudo R^2	0.0132	0.0199	0.1496	0.1497
Sample Average	0.1977	0.1977	0.1977	0.1977

Computing Returns on Capital ▸ Back

	(1)	(3)
	Second-Stage	First Stage
	$\frac{Income_{i,t}}{Avg(Income_{Pre})}$	$\frac{Capital_{i,t}}{Avg(Capital_{Pre})}$
$\frac{Capital_{i,t}}{Avg(Capital_{Pre})}$	0.7995*	
	(0.4710)	
Treatment X Post		0.1020***
		(0.0201)
Household FE	Yes	Yes
District X Month FE	Yes	Yes
Education group X District FE	Yes	Yes
Education group X Month FE	Yes	Yes
Gender group X District FE	Yes	Yes
Gender group X Month FE	Yes	Yes
Age group X District FE	Yes	Yes
Age group X Month FE	Yes	Yes
HH Size group X District FE	Yes	Yes
HH Size group X Month FE	Yes	Yes
# Obs	97,609	97,609
First Stage f-statistic		25.650

- Monthly Return on Capital $= 0.7995 \times \frac{Avg(Income_{Pre})}{Avg(Capital_{Pre})} = 1.84\%$
  - Annualized Return $= 24.39\%$

Comparison of the Estimate with Prior Literature

Back

	Returns on Capital										
	p5	p10	p20	p30	p40	Average	p60	p70	p80	p90	p95
Monthly	0.03%	0.43%	0.91%	1.26%	1.56%	1.84%	2.11%	2.41%	2.76%	3.24%	3.64%
Annualized	0.38%	5.30%	11.53%	16.23%	20.39%	24.39%	28.52%	33.07%	38.60%	46.61%	53.56%

Study	Country	Average Returns on Capital	
		Monthly	Annualized
Udry and Anagol (2006)	Ghana	4.0%	60.1%
De Mel, McKenzie and Woodruff (2008)	Sri Lanka	5.5%	90.1%
Duflo, Kremer and Robinson (2008)	Kenya	4.5%	69.5%
McKenzie and Woodruff (2008)	Mexico	20.0%-33.0%	791.6%-2963.5%
Dupas and Robinson (2013)	Kenya	5.9%	99.0%
Field et al. (2013)	India	13.0%	333.5%
Kremer et al (2013)	Kenya	5.9%	100.0%
Banerjee and Duflo (2014)	India	89.0%	207650.3%

Effect on Credit

Back

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.1091***	0.1295***	0.1685***
	(0.0086)	(0.0160)	(0.0101)
Farmer FE	Yes	Yes	Yes
ZIP $\times$ Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.5256	0.6797	0.7805
Sample Mean	0.618	1.182	396,970

Robustness: Effect on Credit ▸ Back

Loan-level analysis

Dep Var: LN(Loan Amount)	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.1671***	0.1218*	0.1459**	0.1472**	0.1566**
	(0.0584)	(0.0647)	(0.0649)	(0.0674)	(0.0698)
Farmer FE	Yes	Yes	Yes		
Month FE	Yes				
ZIP X Month FE		Yes	Yes	Yes	Yes
ZIP X Bank Type FE			Yes		
Farmer X Bank Type FE				Yes	Yes
Bank Type X Month FE					Yes
# Obs	196,654	196,654	196,654	196,654	196,654
R^2	0.4385	0.514	0.5556	0.5956	0.5995

- Amount of new loans increase by 16% for treatment group

What Does the Additional Credit Finance? Back

The increased credit goes into financing productive capacity

	Panel A: Productive Capacity Loans			Panel B: Non-Productive Capacity Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0886***	0.2169***	0.2813***	0.0064	0.0197	-0.026
	(0.0117)	(0.0087)	(0.0145)	(0.0040)	(0.0121)	(0.0183)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	87,238	87,238	87,238	87,238	87,238	87,238
R^2	0.596	0.705	0.806	0.527	0.608	0.636
Sample Mean	0.316	0.401	245,964	0.430	0.709	149,599

Robustness: What Does the Additional Credit Finance?

The increased credit goes into financing productive capacity

Back

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Productive Loan X Treatment X Post	0.0879***	0.3347**	0.3385***
	(0.0092)	(0.0693)	(0.0445)
Farmer X Post FE	Yes	Yes	Yes
Loan Type X ZIP X Post FE	Yes	Yes	Yes
# Obs	174,476	174,476	174,476
R^2	0.543	0.565	0.678
Sample Mean	0.373	0.555	197,782

Policy's Effect on Income by Credit Constraints ▸ Back

Credit markets play an important role in increasing income

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)
Treatment X Post	0.1261***	0.1390***	0.0080
	(0.0119)	(0.0477)	(0.0080)
Farmer FE	Yes	Yes	Yes
ZIP Code X Month FE	Yes	Yes	Yes
# Obs	2,169,451	1,733,886	433,694
R^2	0.2705	0.2769	0.2712
Sample	Full	No Prior Default	Prior Default
Economic Effect (in ₹)	12,612	16,003	709
Economic Effect ($1 UBI)	2.1	2.7	0.1

- Farmers with prior default are excluded from credit markets

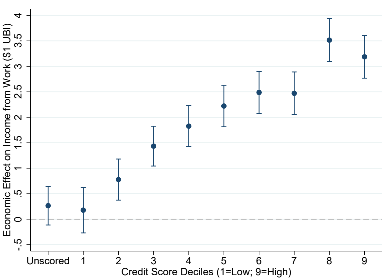
Policy's Effect on Credit by Credit Constraints ▸ Back

No effect on credit for farmers with prior default tag

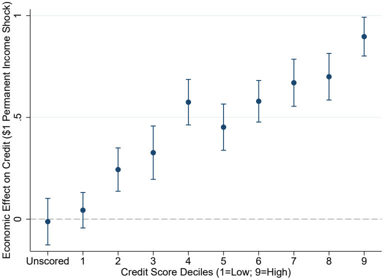
	Panel A: No Prior Default			Panel B: Prior Default		
	(1)	(2)	(3)	(4)	(5)	(6)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.1077***	0.1597***	0.1717***	0.0265	0.0093	-0.0091
	(0.0137)	(0.0090)	(0.0156)	(0.0258)	(0.0316)	(0.0191)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	69,790	69,790	69,790	17,448	17,448	17,448
R^2	0.526	0.699	0.796	0.568	0.682	0.653
Sample Mean	0.614	1.110	410,496	0.611	1.076	256,441

Policy's Effect by Credit Constraints
Back

Effect on income and credit increases with credit scores



(a) Effect on Income



(b) Effect on Credit

Illustration to Compute KCC Limit

Back

Illustration I

A. Small farmer cultivating multiple crops in a year

ASSUMPTIONS

1. **Assumptions**
   - A. Land holding : 2 acres
   - B. Cropping Pattern
     - Paddy - 1 acre (Scale of finance plus crop insurance per acre : ₹.11000)
     - Sugarcane - 1 acre (Scale of finance plus crop insurance per acre : ₹.22,000)
   - C. Investment / Allied Activities
     - i Establishment of 1+1 Dairy Unit in 1st Year () (Unit Cost : ₹ 20,000 per animal)
     - ii Replacement of Pump set in 3rd year (Unit Cost : ₹.30,000)

2. (i) Crop loan Component

Cost of cultivation of 1 acre of Paddy and 1acre of Sugarcane (11,000+22,000)	:	₹.33,000
Add : 10% towards post-harvest / household expense / consumption	:	₹. 3,300
Add : 20% towards farm maintenance	:	₹. 6,600
Total Crop Loan limit for 1st year	:	**₹. 42,900**
Loan Limit for 2nd year		
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 42900 i.e 4300)	:	₹. 4,300
		₹. 47,200

ANNUAL CHANGES TO CREDIT LIMIT

Loan Limit for 3rd year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 47,200 i.e., 4,700)	:	₹. 4,700 **₹. 51,900**
Loan Limit for 4th year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 51,900 i.e 5,200)	:	₹. 5,200 **₹. 57,100**
Loan Limit for 5th year	:	
Add : 10% of the limit towards cost escalation / increase in scale of finance (10% of 57100 i.e 5700)	:	₹. 5,700 **₹. 62,800**
Say ....(A)	:	**₹. 63,000**

(ii) **Term loan component :**

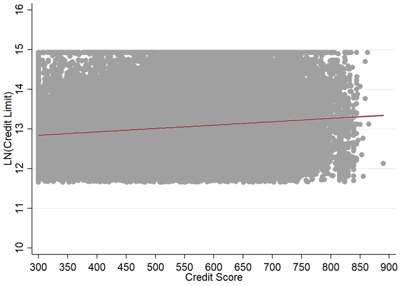
1st Year : Cost of 1+1 Dairy Unit		:	₹. 40,000
3rd Year : Replacement of Pumpset :		:	₹. 30,000
Total term loan amount	....(B)	:	**₹. 70,000**
Maximum Permissible Limit /		:	**₹. 1,33,000**
Kisan Credit Card Limit (A) +(B)		:	**Rs. 1.33 lakh**

Note: Drawing Limit will be reduced every year based on repayment schedule of the term loan(s) availed and withdrawals will be allowed up to the drawing limit.

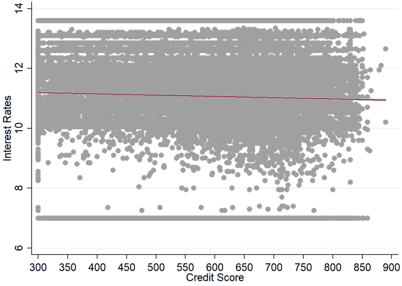
- Illustration taken from RBI Master Circular - Kisan Credit Card (KCC) scheme LINK

Kisan Credit Cards & Credit Worthiness ▸ Back

KCC products are insensitive to credit worthiness



(a) Credit Limit



(b) Interest Rates

Policy's Effect on KCC Limits and Interest Rates
Back

KCC credit limits and interest rates do not respond to the policy of the treatment group

	(1)	(2)
	LN(Credit Limit)	Interest Rates
Treat X Post	0.0018	-0.0119
	(0.0037)	(0.0025)
Farmer FE	Yes	Yes
ZIP Code X Post FE	Yes	Yes
# Obs	126,432	126,432
R^2	0.9970	0.9784
Sample Mean	12.7457	11.1181

Policy's Effect on Utilization Rate for KCC

Back

Utilization of Kisan Credit Cards increases by 6.75 pp

Dep Var: Utilization Rate	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.0735***	0.0735***	0.0788***	0.0764***	0.0675***
	(0.0258)	(0.0258)	(0.0261)	(0.0230)	(0.0233)
Treatment	-0.0055***	-0.0055***	-0.0064***		
	(0.0004)	(0.0004)	(0.0006)		
Post	-0.0008				
	(0.0006)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	1,512,367	1,512,367	1,512,367	1,512,367	1,512,367
R^2	0.0001	0.0005	0.0439	0.2688	0.2938
Sample UR Mean	0.2134	0.2134	0.2134	0.2134	0.2134
Sample KCC Limit	397,161.20	397,161.20	397,161.20	397,161.20	397,161.20
Increased Usage	29,191.35	29,191.35	31,296.30	30,343.12	26,808.38

Assumption required to interpret applications as demand

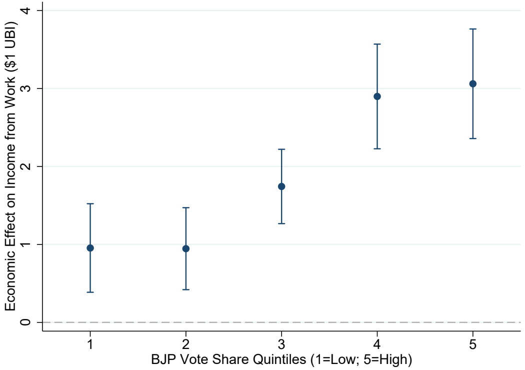
Individuals do not anticipate loose credit supply

Back

Effect of PMKSN on Expected Lending Standards	All Respondents	PMKSN Recipients	
		Yes	No
Tighten	43.37	42.65	44.18
No Change	30.23	32.52	27.64
Loosen	26.41	24.83	28.19
# Obs (Respondents)	3,090	1,639	1,451

Policy's Effect by Trust in Government Commitment ▸ Back

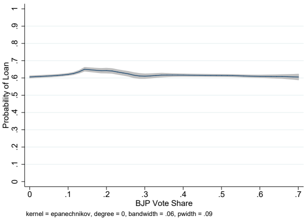
Effect higher when expectations of future risk protection are higher



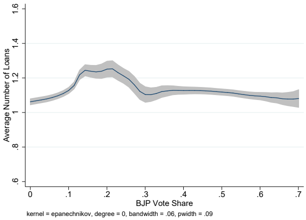
- Trust ↑ ⇒ Prob. of Continuance ↑ ⇒ Future risk protection ↑
- Identifying Assumption: Credit supply policy is centralized, whereas demand is decentralized ▸ Discussion ▸ Interest rates

Lending in Pre-Period ▸ Back

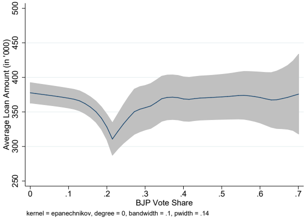
Lending policy does not vary with BJP vote share



(a) Probability of Loan



(b) # Loans



(c) Loan Amount

Heterogeneous Effect of the Policy on Interest Rates ▸ Back

BJP vote share

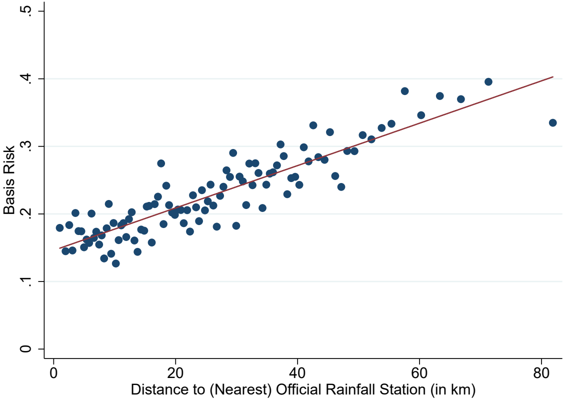
Dep Var: Interest Rates	(1)	(2)	(3)
BJP Vote Share X Treatment X Post	-0.0030		
	(0.0347)		
High Rainfall Risk X Treatment X Post		-0.0093	
		(0.0249)	
High Basis Risk X Treatment X Post			-0.0062
			(0.0075)
Treatment X Post	0.0194	0.0114	0.0207*
	(0.0331)	(0.0319)	(0.0109)
Farmer FE	Yes	Yes	Yes
ZIP Code X Post FE	Yes	Yes	Yes
# Obs	166,432	166,432	166,432
R^2	0.9567	0.9572	0.9449

Heterogeneous Effect of the Policy on Interest Rates ▸ Back

Rainfall risk

Dep Var: Interest Rates	(1)	(2)	(3)
BJP Vote Share X Treatment X Post	-0.0030		
	(0.0347)		
High Rainfall Risk X Treatment X Post		-0.0093	
		(0.0249)	
High Basis Risk X Treatment X Post			-0.0062
			(0.0075)
Treatment X Post	0.0194	0.0114	0.0207*
	(0.0331)	(0.0319)	(0.0109)
Farmer FE	Yes	Yes	Yes
ZIP Code X Post FE	Yes	Yes	Yes
# Obs	166,432	166,432	166,432
R^2	0.9567	0.9572	0.9449

Basis Risk in Rainfall Insurance Markets ▸ Back



- Basis risk is computed as the $1 - R^2$ of the regression of rainfall in a zipcode and the nearest official rainfall station
- Basis risk increases with the distance of zipcode from rainfall station à la Mubarak & Rosenzweig (2012, 2013)

Heterogeneous Effect of the Policy on Interest Rates

Back

Basis risk

Dep Var: Interest Rates	(1)	(2)	(3)
BJP Vote Share X Treatment X Post	-0.0030		
	(0.0347)		
High Rainfall Risk X Treatment X Post		-0.0093	
		(0.0249)	
High Basis Risk X Treatment X Post			-0.0062
			(0.0075)
Treatment X Post	0.0194	0.0114	0.0207*
	(0.0331)	(0.0319)	(0.0109)
Farmer FE	Yes	Yes	Yes
ZIP Code X Post FE	Yes	Yes	Yes
# Obs	166,432	166,432	166,432
R^2	0.9567	0.9572	0.9449

Basis Risk & Low Insurance Demand ▸ Back

- Basis risk is an important determinant for taking up index insurance by farmers (see Robles, 2021)
  - Hill, Robles Ceballos (2016) [India]
    - Demand for weather insurance in falls with basis risk
    - Doubling the distance to a reference weather station decreases demand by 18%
  - Mubarak and Rosenzweig (2013) [India]
    - Every kilometer increase in the (perceived) distance of the weather station demand for formal index insurance drops by 6.4 percent
  - Other evidence from Africa: Karlan et al. (2014), Jensen, Barrett, and Mude (2016)

- Index insurance was mandatory while taking a crop loan or KCC under Pradhan Mantri Fasal Bima Yojana (PMFBY)
  - Note: This mandate was scrapped in 2021

Policy's Effect on Perceived Financial Condition

Back

Treatment households report better financial conditions

	(1)	(2)
	Financial Condition Today, Relative to Last Year	Financial Condition Next Year, Relative to Last Year
Treatment X Post	0.0432***	0.0443***
	(0.0142)	(0.0128)
Household FE	Yes	Yes
Education group X District FE	Yes	Yes
Education group X Month FE	Yes	Yes
Gender group X District FE	Yes	Yes
Gender group X Month FE	Yes	Yes
Age group X District FE	Yes	Yes
Age group X Month FE	Yes	Yes
HH Size group X District FE	Yes	Yes
HH Size group X Month FE	Yes	Yes
District X Month FE	Yes	Yes
# Obs	159,940	159,940
R^2	0.616	0.584

Effect on Farmer Suicides

Back

Farmer suicides decrease by 6.63% after the policy

$$\frac{y_{z,f,p}}{Avg(y)_{Pre}} = \beta \cdot Farmer_f \cdot Post_t + \theta_{z,f} + \theta_{z,t} + \varepsilon_{z,f,t}$$

Dep Var: $\frac{y_{z,f,p}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Farmer X Post	-0.0663***	-0.0663***	-0.0663***	-0.0663***
	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Farmer	-0.5973***	-0.5973***	-0.5973***	
	(0.0343)	(0.0343)	(0.0343)	
Post	0.0883***			
	(0.0149)			
ZIP Code FE		Yes		
Post FE		Yes		
ZIP Code X Post FE			Yes	Yes
ZIP Code X Farmer FE				Yes
# Obs	2,220	2,220	2,220	2,220
R^2	0.2096	0.6097	0.6298	0.9801
Sample Mean	16.271	16.271	16.271	16.271

Effect on Farmer Suicides Due to Debt ▸ Back

Farmer suicides due to debt decrease by 6.42% after the policy

$$\frac{y_{z,d,p}}{Avg(y)_{Pre}} = \beta \cdot Debt_d \cdot Post_t + \theta_{z,d} + \theta_{z,t} + \varepsilon_{z,d,t}$$

Dep Var: $\frac{y_{z,d,p}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Debt X Post	-0.0642*	-0.0642*	-0.0642*	-0.0642*
	(0.0348)	(0.0348)	(0.0348)	(0.0348)
Debt	-0.0281	-0.0281	-0.0281	
	(0.0412)	(0.0412)	(0.0412)	
Post	0.0092			
	(0.0267)			
ZIP Code FE		Yes		
Post FE		Yes		
ZIP Code X Post FE			Yes	Yes
ZIP Code X Debt FE				Yes
# Obs	1,384	1,384	1,384	1,384
R^2	0.0038	0.4892	0.5792	0.9227
Sample Mean	5.038	5.038	5.038	5.038

Effect of Treatment on Physical Effort ▸ Back

66% of treated farmers increase their physical effort after the policy

Effect of PMKSN on Physical effort in Agriculture	All Respondents	PMKSN Recipients	
		Yes	No
Increase	66.12	63.15	69.47
Decrease	16.93	17.21	16.61
No Change	16.96	19.65	13.92
# Obs (Respondents)	3,090	1,639	1,451

Cash-in-Hand Effect on Investment

Back

Likely to be limited to 6% of the total effect

- Some examples of assets purchased by farmers
  - Tractor: ₹700,000
  - Cow: ₹150,000
  - Two-wheeler: ₹80,000
    - These amounts are very large relative to ₹6,000

- Another example: 21-35 HP tractor, 5 ltr/hr (minimum), 20 hours (minimum)
  - Cost of Diesel = ₹6,700 per cultivation season at ₹67 per ltr

Extent of Negative Income (*Hammock*) Effect

▸ Back

17% of farmers indicate decreasing their physical effort due to the policy

Effect of PMKSN on Physical effort in Agriculture	All Respondents	PMKSN Recipients	
		Yes	No
Increase	66.12	63.15	69.47
Decrease	16.93	17.21	16.61
No Change	16.96	19.65	13.92
# Obs (Respondents)	3,090	1,639	1,451

Effect on Leisure & Entertainment Spending ▸ Back

21% of farmers indicated increasing their spending on leisure & entertainment

Effect of PMKSN on Leisure & Entertainment Spending	All Respondents	PMKSN Recipients	
		Yes	No
No Change	54.40	54.30	54.51
Decrease	24.08	23.49	24.74
Increase	21.52	22.21	20.74
# Obs (Respondents)	3,090	1,639	1,451

Survey Questions ▸ Back

- Add'l (Additional) worry of bad times due to debt
  - With respect to your borrowing, please tell us how worried you are about bad times when you have debt obligation relative to no debt obligations. Use a scale from 1 to 10, where 10 means you are "very worried" and 1 means you are "not at all worried." You can use any number between 1 and 10 to rate yourself on the scale. You can think of bad times as times of drought, hailstorm, etc.

- How often do you worry?
  - How often (if any) do you worry about bad times because of a debt obligation? If you do not have a debt obligation, please answer this question as if you had a debt obligation. You can think of bad times as times of drought, hailstorm, etc.
    - ⋆ (a) No additional worry due to debt; (b) Once every month; (c) Once a week; (d) Daily; (e) Constantly

Survey Questions ‣ Back

- Why do you worry?
  - When you think about taking an agricultural loan, what (if anything) concerns you the most about the loan? If you don't have a loan, please answer this question as if you had a loan.
    - ⋆ I am most worried about defaulting on the loan during bad times such as drought
    - ⋆ I am most worried about meeting basic needs of food clothing and shelter, after I repay the loan EMI during bad times such as drought
    - ⋆ I can take a loan without any concern or worry
- Why worry about default?
  - Please tell us which of the following issues concern you the most about being unable to repay a loan
    - ⋆ Your land and other assets will be taken away from you
    - ⋆ You will not be able to show your face to family and friends
    - ⋆ You will have to go to jail or be stuck in a court case
    - ⋆ You will never be able to borrow again cheaply
    - ⋆ You will be forced to do something bad such as hurt yourself

Effect on Hedging: Agricultural Diversification

Back

1% increase in the number of district-level beneficiaries reduces agricultural diversification by 1.4-1.9%

	(1)	(2)	(3)	(4)
	$1 - \sum s_i^2$	$\sum s_i \cdot LN(\frac{1}{s_i})$	$1 - s_1 - \sum s_i^2 \cdot (2 - s_i)$	$- 2 \sum i \cdot s_i$
LN(# Beneficiaries) X Post	-0.0139***	-0.0188***	-0.0192***	-0.0182***
	(0.0033)	(0.0030)	(0.0036)	(0.0024)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Obs	2,272	2,272	2,272	2,272
R^2	0.8271	0.8516	0.8519	0.8862
Sample Mean	0.5997	0.5437	0.5800	0.2978

Effect on Hedging: Cash Crop Cultivation ▸ Back

Districts with greater # PMKSN beneficiaries have a greater cultivated area under cash crops after the policy

Dep Var: Share of GSA Under Cash Crops	(1)	(2)	(3)
LN(# Beneficiaries) X Post	0.0086***	0.0086***	0.0105***
	(0.0027)	(0.0027)	(0.0024)
LN(# Beneficiaries)	0.0211***	0.0211***	
	(0.0024)	(0.0024)	
Post	-0.0751***		
	(0.0280)		
Year FE		Yes	Yes
District FE			Yes
# Obs	2,276	2,276	2,276
R^2	0.0595	0.0600	0.9006
Sample Mean	0.0732	0.0732	0.0732

Effect on Agricultural Labor Wages

Back

No effect on wages

	(1)	(2)	(3)	(4)	(5)
	LN(Wage)	LN(Wage)	LN(Wage)	g(Wage)	g(Wage)
Agricultural Sector X Post	0.0006	0.0007	0.0003	-0.0011	-0.0002
	(0.0049)	(0.0022)	(0.0012)	(0.0009)	(0.0009)
Agricul;tural Sector	-0.2060***			0.0016***	
	(0.0098)			(0.0006)	
Post	0.0248***			0.0029***	
	(0.0050)			(0.0009)	
LN(Wage)$_{t-1}$			0.5333***		
			(0.0139)		
District X Month X Gender		Yes	Yes		Yes
District X Labor Type X Gender FE		Yes	Yes		Yes
# Obs	124,363	124,363	124,363	124,363	124,363
R^2	0.0687	0.9705	0.9787	0.0002	0.4485
Sample Mean	5.6951	5.6951	5.6951	0.0040	0.0040
Sample SD	0.3784	0.3784	0.3784	0.0846	0.0846

Why Does The Supply Side Show Little Response?

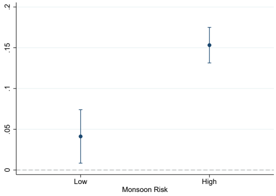
- Credit supply can depend on future cash flows (Stiglitz & Weiss, 1981; Holmstrom & Tirole, 1997)
  - Key Assumption:
  - Contractibility of future cash flows
  - Practicality of ex-post lender reorganization
    - ★ However, payments from the government cannot be garnished
    - ★ Costly to reorganize small firms (Lian & Ma, 2021)

- Moreover, lenders focus on three attributes for agricultural lending:
  - Credit score & history
  - Collateral
  - Expected yield to compute debt to income ratio
    - ★ All are based on historical data and any structural changes are not reflected in these metrics *in the short-run*

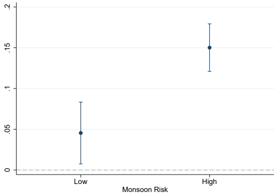
Role of Downside Risk ▸ Back

Marginal benefit of guaranteed income is higher when downside risk is high

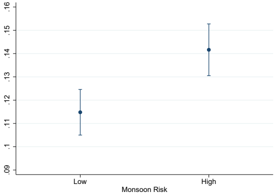
$$\frac{y_{i,p}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t}$$



(a) Prob of New Loan



(b) # Loans



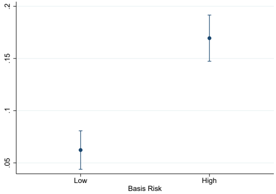
(c) Loan Amount

- Identifying Assumption: Credit supply does not respond asymmetrically to the policy by risk ▸ Interest rates

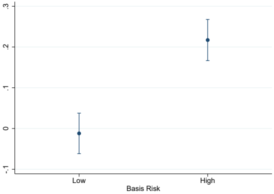
Role of Incomplete Insurance Markets ▸ Back

Marginal benefit of guaranteed income is higher when the risk is uninsurable

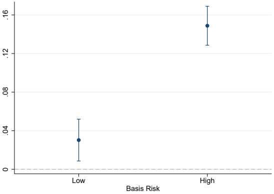
$$\frac{y_{i,p}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t}$$



(a) Prob of New Loan



(b) # Loans



(c) Loan Amount

- Incomplete insurance measured by ZIP level basis risk ▸ Discussion
- Low insurance take-up when basis risk is high ▸ Literature
- Identifying Assumption: Credit supply does not respond asymmetrically to the policy by basis risk ▸ Interest rates

Effect by Trust in Government Commitment ‣ Back

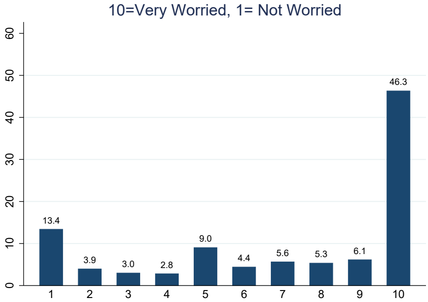
Effect higher when expectations of future risk protection are higher ‣ Income Results

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
BJP Vote Share X Treatment X Post	0.3064**	0.2971**	0.5280***
	(0.0882)	(0.0637)	(0.0522)
Treatment X Post	0.0204***	0.0483	0.0322
	(0.0019)	(0.0280)	(0.1106)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.525	0.680	0.781

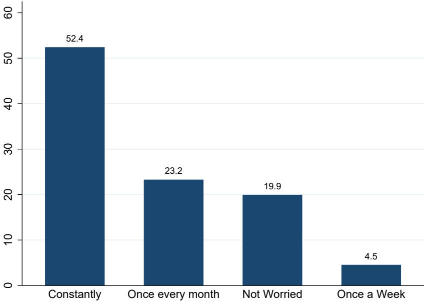
- Trust $\uparrow \Rightarrow$ Prob. of Continuance $\uparrow \Rightarrow$ Future risk protection $\uparrow$
- Identifying Assumption: Credit supply policy is centralized, whereas demand is decentralized ‣ Discussion ‣ Interest rates

What Impedes Credit Demand? ▸ Questions

Worry about the effect of credit contracts during bad times



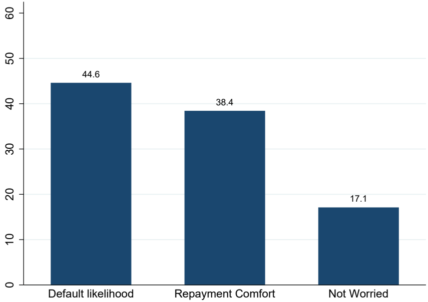
(a) Add'l worry of bad times due to debt



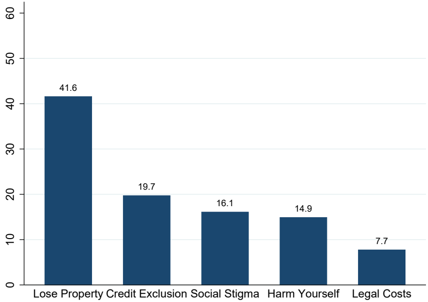
(b) How often do you worry?

What Impedes Credit Demand? Questions

Worry about the effect of credit contracts during bad times



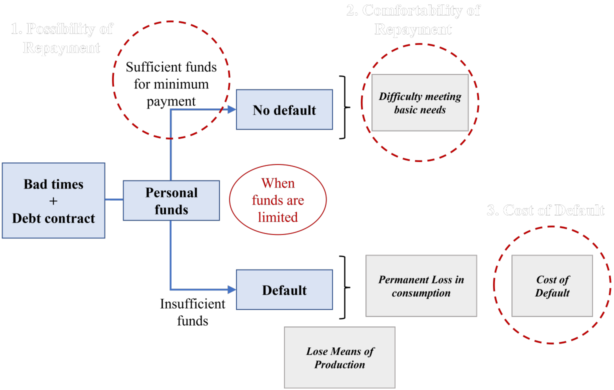
(a) Why do you worry?



(b) Why worry about default?

What Impedes Credit Demand?

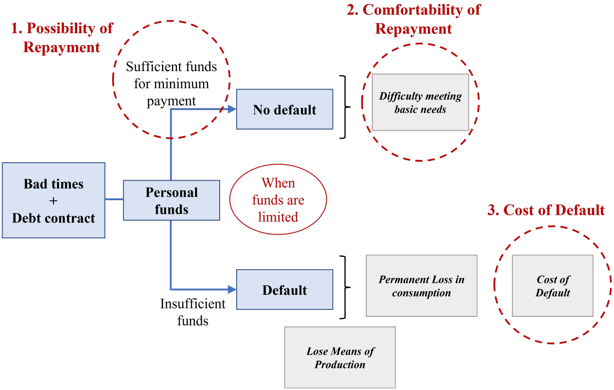
Credit contracts increase downside risk



- Key Friction: Debt contracts + Limited funds ⇒ More downside risk
  - ⇒ Low credit demand

What Impedes Credit Demand?

Credit contracts increase downside risk



- Key Friction: Debt contracts + Limited funds $\Rightarrow$ More downside risk
  - $\Rightarrow$ Low credit demand

Other Results

- Other Channels
  - Cash-in-hand effect on investment ▸ Discussion
  - *Physiological productivity* effect & the *psychological income effect*
    - ★ Transfers $\Rightarrow$ Nutrition $\uparrow$ & Stress $\downarrow$ $\Rightarrow$ Physical Effort $\uparrow$ à la Banerjee, Karlan, Trachtman & Udry (2020) ▸ Discussion

- Ancillary Results
  - How significant is the negative income (*hammock*) effect? ▸ Discussion
  - Effect on hedging activity: Agricultural diversification ▸ Results; Cash crop cultivation ▸ Results
  - Effect on leisure & entertainment spending ▸ Discussion
  - Effect on extreme distress: Farmer suicides ▸ Results ▸ Results
  - Effect on consumption, saving & default ▸ Results
  - Effect on agricultural labor wages ▸ Discussion

Contribution #1: Risk is the binding constraint

- Biggest impediment(s) to investment by small firms
  1. Borrowing Constraints (Evans & Jovanovic, 1989)
  2. Risk (Hurst & Lusardi, 2004)

- Increasing access of credit markets can resolve (1)
  - But, debt contracts impose cost of default in bad states (Townsend, 1979; Diamond, 1991)
    - Risk + Default cost ⇒ Credit Demand ↓

- <u>This paper:</u> Safety nets ↑ ⇒ Credit Demand ↑
  - <u>Risk may be the binding constraint</u>

- Related works:
  - Rosenzweig & Wolpin (1993), Hurst & Lusardi (2004), Dercon & Christiaensen (2011), Bianchi & Bobba (2013), Field et al. (2013), Karlan et al. (2014), Emerick et al. (2016), Lane (2020), Donovan (2021)

Contribution #2: Explanation for *Euler Equation Puzzle*

- **Puzzle:**
  - ★ Returns to capital for micro-enterprises are high: Banerjee & Duflo (2005), Duflo et al. (2008), de Mel, McKenzie, & Woodruff (2008, 2012), , McKenzie & Woodruff (2008), Kremer et al. (2013), Blattman et al. (2014), Fafchamps et al. (2014)
  - ★ Improving access to credit does not increase loan take-up: Banerjee (2013), Banerjee, Karlan, & Zinman (2015), Meager (2018)
  - ▸ Why are micro-entrepreneurs leaving money on the table? Banerjee & Duflo (2007), Woodruff (2018), Kremer, Rao & Schilbach (2019)

- **Answer:** Uninsured risk+ High risk-aversion $\Rightarrow$ $\underbrace{\text{Under investment}}_{\text{Leaving money on the table}}$
  - ▸ Lubricating demand-side frictions is essential to stimulate investment
    - ★ Safety Nets such as guaranteed income is one way to do that ▸ Other