# Political Partisanship and the Transmission of Fiscal Policy

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# Motivation

Since the start of 21st century, increased political polarization in

- Traditional media
- Social media
- Legislative and executive bodies

Polarization in government *directly* affects fiscal policies/reforms
(Allcott et al. (2020), Aghion et al. (2004), Alesina and Rosenthal (1989))

# Motivation

Partisanship can affect the success of gov't policies *indirectly*

Citizens' participation in govt. policies is crucial for their success
(Ex. Covid Mask Mandates)

Participation depends on agents' subjective beliefs about the benefits
(Barrios and Hochberg (2020a); Cookson et al (2020); Dahl et al (2021))

Partisanship affect the decisions of expert/professionals
(Kempf et al. (2021); Kempf and Tsoutsoura (2021); Fos et al. (2022))

Likely to affect decisions of non-sophisticated decision makers when:

- Benefits from participating in govt. policies are difficult to compute
- Individuals lack financial literacy to compute the benefits
- The success of govt. policies can affect future electoral outcomes

# This Paper-I

Study if and how fiscal-policy program uptake relates to partisanship

**Biggest challenge.** The setting should allow for:

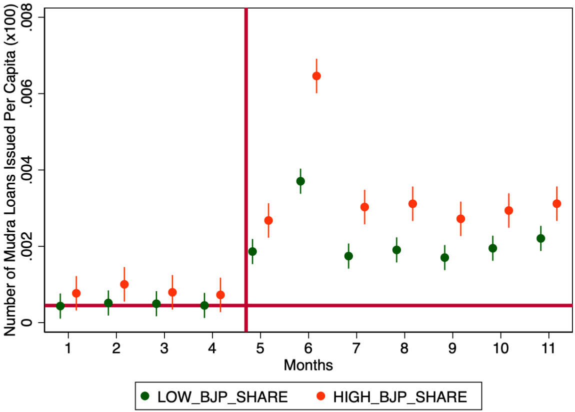
- Disentangling citizens' support for the ruling party vs. governments catering their policies to their supporters
- Control for unobserved time-invariant and time-varying drivers of economic activities correlated with partisanship

# This Paper-II

Setting: large-scale government-guaranteed loan program

- *Mudra Loans*, launched April 2015
- Costly take-up for citizens
- Broadly covered by traditional and social media
- Starting October 2015, a heavy promotional campaign by PM Modi
- Participation started representing support for Modi and BJP

# This Paper-III




→ Strong divergence in program uptake between areas with:

- High support for Modi in 2014 elections (High_BJP_Share)
- Low support for Modi in 2014 elections (Low_BJP_Share)

# This Paper-IV

- Show our results are not explained by:
  - Borrowers' risk
  - Interest rates
  - Subsequent default rates
  - Access to bank branches
  - Regular-loan issuance (proxying local demand for credit)

  → Rules out changes in local economic activity drive results

- The effects are larger in contested districts
  → Show-your-support effect may be at play

- Effect is driven by individual borrowers and sole proprietorships (not large corporations)

# Related Literature

- Effect of partisanship on economic decisions

  (Barrios and Hochberg (2020a); Cookson et al (2020); Dahl et al (2021))

  (Kempf et al. (2021); Kempf and Tsoutsoura (2021); Fos et al. (2022))

  → Focus on the uptake of fiscal policy programs

- Relation between fiscal policy and political partisanship
  - Use of fiscal policy to increase political support
    (Manacorda et al. (2011), Levitt & Snyder (1995), Duchin & Hackney (2020))
  - Across subpopulations of the electorate
    (Stokes (2005), Finan and Schechter (2012), Gonzalez-Ocantos et al. (2012))

  → We study the reverse channel

# Mudra Loan Program

**Goals:**

- “Fund the unfunded” by extending affordable credit to MSMEs (historically, did not have access to the formal financial system)
- Register and regulate all the Microfinance Institutions (MFIs)

**Features:**

- Until April 2016, limited non-farming sectors
- Mudra loans are not backed by any form of collateral
- Not charged processing fees
- Maximum loan offered under the program is 1 million Rupees
- Interest rates charged following RBI guidelines

# October 2015 Political Campaign-I

**April 2015:**

- Approval and implementation of the Mudra Loan program
- Covered prominently by national and local media.

**September-October 2015:**

- Media and physical political campaign featuring Modi
- Rallies in 50 different locations
- Portrayed participation as an act of support for the party
- In the aggregate, the campaign increased Mudra take-up rates
  - From April to August 2015, *Millions* disbursed
  - By the end of 2015, *Billions* disbursed

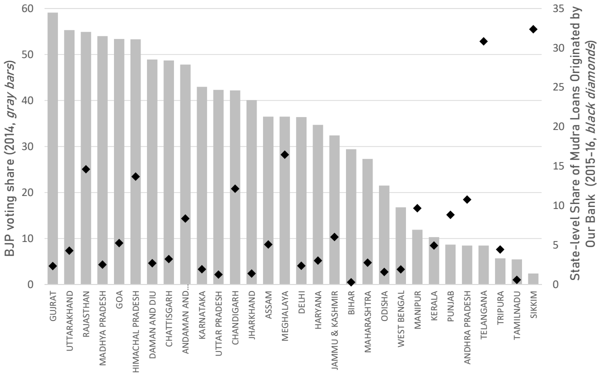
# October 2015 Political Campaign-II





# Data-I

- Core dataset: 20% random sample of the loans issued by SBI
- Dates: April 2015 and March 2016.
- SBI is a public sector bank. This feature unlikely to drive our results:
  - SBI accounts for 25% of deposits in India and 11% of Mudra loans
  - Mudra loans not disproportionately originated in high-bjp-support areas



# Data-II

Loan characteristics we observe:

- Whether it was issued under the Mudra program
- Date of issuance
- Loan amount
- Interest rate
- Categorization of the loan performance

Borrower characteristics we observe:

- Borrower categorization (32 categories)
- Sector in which the borrower operates
- Pincode of the borrower
- Borrower's gender

We match loan-level data with election results at the electoral district level

# Summary Statistics

**Panel A. Loan Characteristics**

| | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Loan Amount | 165,734 | 123,437 | 194,299 | 30,000 | 50,000 | 100,000 |
| Interest Rate | 165,734 | 9.78 | 3.85 | 9.70 | 11.25 | 12.30 |
| Non-performing Flag | 165,734 | 0.59 | 0.49 | 0.00 | 1.00 | 1.00 |
| Female | 123,372 | 0.23 | 0.42 | 0.00 | 0.00 | 0.00 |

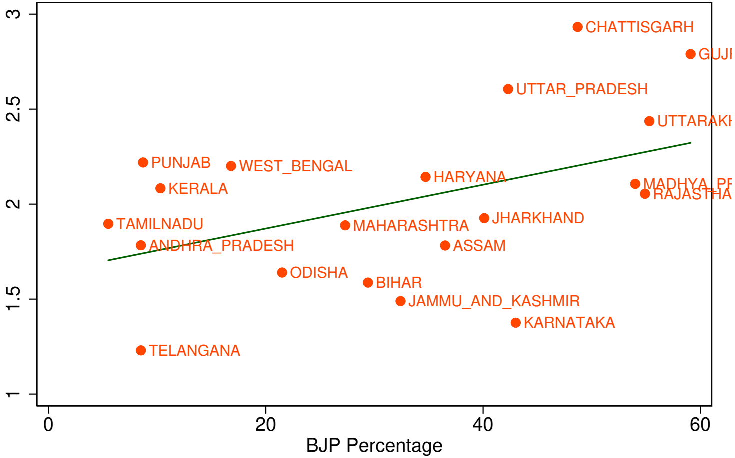
**Panel B. Loan Classification**

| | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Shishu Dummy | 163,354 | 0.98 | 0.12 | 1.00 | 1.00 | 1.00 |
| Individual Dummy | 165,726 | 0.87 | 0.33 | 1.00 | 1.00 | 1.00 |
| Trade and Services Dummy | 163,354 | 0.94 | 0.23 | 1.00 | 1.00 | 1.00 |

# Raw Data and Motivational Evidence-I

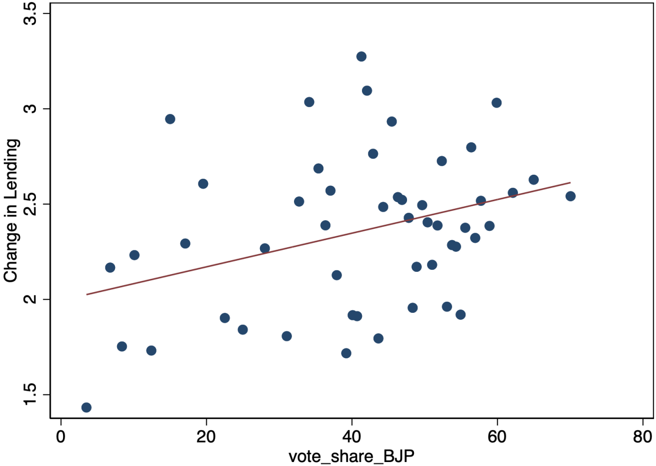
1. Growth in MUDRA loans during campaign versus before campaign
2. Relate it to average BJP vote share in the 2014 general elections.

**State Level:**



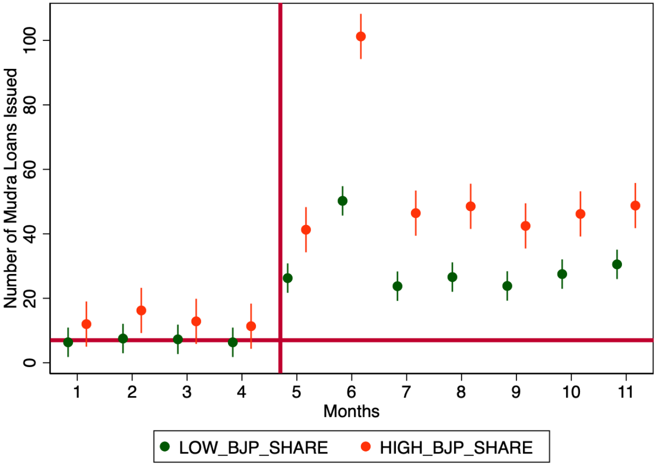
# Raw Data and Motivational Evidence-II

‘ **Electoral District Level:**



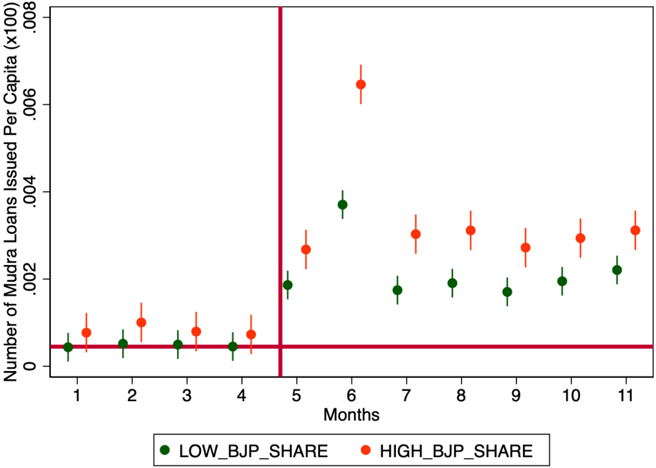
# Raw Data and Motivational Evidence-III

- Compute total number of Mudra loans in each district
- Average across low- and high-bjp-support areas in 2014 elections
- Vertical line, start of the promotion campaign



# Raw Data and Motivational Evidence-IV

Repeating analysis but working with Loans per capita



# Multivariate District-Level Analysis-I

$$\begin{aligned}
\textit{Number/Value Loans}_{j,t} = {} & \alpha_j + \beta_1 \times \textit{BJP Share}_j \times \textit{During Campaign}_t \\
& + \beta_2 \times \textit{BJP Share}_j \times \textit{After Campaign}_t \\
& + \gamma_1 \times \textit{During Campaign}_t \\
& + \gamma_2 \times \textit{After Campaign}_t + \delta \times \textit{BJP Share}_j + X'_{j,t}\zeta + \epsilon_{j,t},
\end{aligned}$$

where

- $\textit{Number/Value Loans}_{j,t}$ in district $j$ and month $t$
- $\alpha_j$ is a full set of district-level fixed effects
- $\textit{BJP Share}_j$ is the voting share for the BJP party in electoral district $j$
- $\textit{During Campaign}_t$ is equal to 1 for October and November 2015
- $\textit{After Campaign}_t$ is equal to 1 for after November 2015

# Multivariate District-Level Analysis-II

| | Number of Loans | | Value of Loans | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| BJP Vote Share× During Campaign | 15.25** (2.95) | 15.29** (2.94) | 0.96*** (3.70) | 0.96*** (3.74) |
| BJP Vote Share× After Campaign | 6.18*** (3.22) | 6.21*** (3.26) | 0.47 (1.68) | 0.48 (1.73) |
| During Campaign | 43.06** (2.59) | 45.00** (2.42) | 3.00*** (3.94) | 3.24*** (3.49) |
| After Campaign | 24.03*** (4.03) | 24.55*** (4.10) | 3.46*** (6.16) | 3.48*** (6.28) |
| BJP Vote Share | — — | — — | — — | — — |
| Interacted Controls | NO | YES | NO | YES |
| Constant | 15.46** (2.77) | 15.46** (2.78) | 2.29*** (6.67) | 2.29*** (6.71) |
| R-Square | 0.63 | 0.63 | 0.67 | 0.67 |
| Electoral District FE | ✓ | ✓ | ✓ | ✓ |
| Obs | 3,870 | 3,870 | 3,870 | 3,870 |

# Multivariate Loan-Level Analysis-I

$$
\begin{aligned}
\textit{Loan Issued}_{i,j,t} = \alpha &+ \beta_1 \times \textit{BJP Share}_j \times \textit{During Campaign}_t \\
&+ \beta_2 \times \textit{BJP Share}_j \times \textit{After Campaign}_t \\
&+ \gamma_1 \times \textit{During Campaign}_t \\
&+ \gamma_2 \times \textit{After Campaign}_t + \delta \times \textit{BJP Share}_j + \epsilon_{i,j,t},
\end{aligned}
$$

where:

- $\textit{Loan Issued}_{i,j,t}$ is an indicator variable equal to 1 if the loan $i$ in electoral district $j$ was issued on month $t$

Coefficients of interest are:

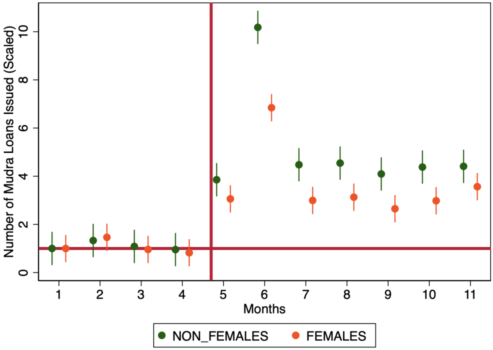
- $\beta_1$: differential Mudra loan issuance during the promotional campaign
- $\beta_2$: differential Mudra loan issuance after the promotional campaign

# Multivariate Loan-Level Analysis-II

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| BJP Vote Share× During Campaign | 0.01** | 0.01** | 0.01*** | 0.01*** |
| | (3.04) | (3.05) | (3.22) | (3.25) |
| BJP Vote Share× After Campaign | -0.00 | -0.00 | -0.00 | -0.00 |
| | (-0.46) | (-0.45) | (-0.68) | (-0.68) |
| During Campaign | 0.12** | 0.12** | 0.14** | 0.14** |
| | (2.58) | (2.57) | (2.43) | (2.43) |
| After Campaign | 0.07*** | 0.07*** | 0.06*** | 0.06*** |
| | (4.66) | (4.66) | (4.10) | (4.10) |
| BJP Vote Share | -0.00 | -0.00 | -0.00 | — |
| | (-0.69) | (-0.55) | (-0.49) | — |
| Constant | 0.04*** | 0.04** | 0.04* | 0.04** |
| | (3.27) | (2.37) | (2.07) | (2.26) |
| R-Square | 0.03 | 0.03 | 0.03 | 0.03 |
| Loan Characteristics | | ✓ | ✓ | ✓ |
| Demographic Controls | | | ✓ | ✓ |
| Electoral District FE | | | | ✓ |
| Obs | 1,395,240 | 1,375,902 | 1,033,010 | 1,033,010 |

# Heterogeneity Results using Female Borrowers

- Ideally, we would use individual-level variation in support for Modi
- BJP historically low appeal with women
- If results demand-driven, females should respond less to campaign
- Focus on High-BJP-support districts




We confirm these results in formal multivariate regression tests

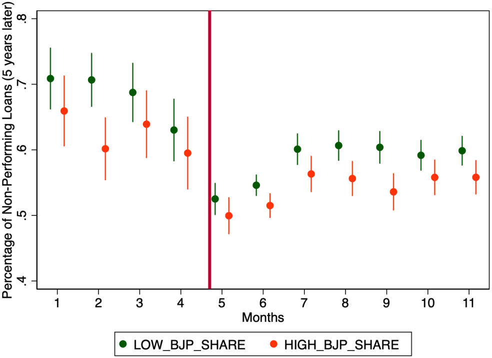
# Assessing and Ruling Out Supply Channels-I

**Channel 1: Access to Finance Channel**

- High-BJP-support areas do not have more SBI bank branches

**Channel 2: Political Support By Loan Officers**

- Lending standards were not laxer in High-BJP-support areas




We confirm these results in formal multivariate regression tests

# Assessing and Ruling Out Supply Channels-IV

**Channel 3: Pressure by BJP-run local governments**

Estimate regression below in BJP- and non-BJP-ruled electoral districts

$$\begin{aligned} \textit{Loan Issued}_{i,j,t} = {} & \alpha + \beta_1 \times \textit{BJP Share}_j \times \textit{During Campaign}_t \\ & + \beta_2 \times \textit{BJP Share}_j \times \textit{After Campaign}_t \\ & + \gamma_1 \times \textit{During Campaign}_t \\ & + \gamma_2 \times \textit{After Campaign}_t + \delta \times \textit{BJP Share}_j + X'_{j,t}\zeta + \epsilon_{i,j,t}, \end{aligned}$$

where:

- $\textit{Loan Issued}_{i,j,t}$ is an indicator variable equal to 1 if the loan $i$ in electoral district $j$ was issued on month $t$

Coefficients of interest are:

- $\beta_1$: differential Mudra loan issuance during the promotional campaign
- $\beta_2$: differential Mudra loan issuance after the promotional campaign

# Assessing and Ruling Out Supply Channels-V

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **BJP ruled** | **Non-BJP ruled** | **BJP ruled** | **Non-BJP ruled** |
| BJP Vote Share× During Campaign | 0.02* (1.95) | 0.02** (2.66) | 0.02** (2.49) | 0.02** (2.99) |
| BJP Vote Share× After Campaign | -0.01 (-0.85) | -0.01** (-2.75) | -0.01 (-0.91) | -0.01* (-1.97) |
| During Campaign | 0.11** (2.64) | 0.14** (2.51) | 0.13** (2.44) | 0.16** (2.41) |
| After Campaign | 0.08*** (6.01) | 0.05*** (3.48) | 0.07*** (5.50) | 0.05*** (3.25) |
| BJP Vote Share | -0.00 (-0.38) | 0.00 (0.47) | — — | — — |
| Constant | 0.04*** (3.66) | 0.05*** (3.53) | 0.04** (2.31) | 0.04* (2.02) |
| R-Square | 0.03 | 0.03 | 0.03 | 0.03 |
| Loan Characteristics | | | ✓ | ✓ |
| Demographic Controls | | | ✓ | ✓ |
| Electoral District FE | | | ✓ | ✓ |
| Obs | 727,353 | 656,502 | 503,580 | 518,793 |

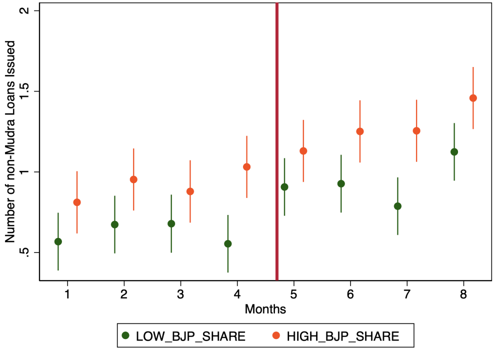
# Assessing Demand Channels-I

**Channel 1. Unobserved Shocks to the Demand for Loans**

- Unlikely unobservables differentially hit various areas during MUDRA
- BUT Modi may have promoted MUDRA program strategically

Falsification test:

- Use loans over 1 million rupees (do not qualify for MUDRA)

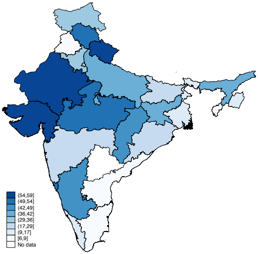


# Assessing Demand Channels-II

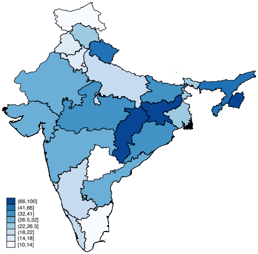
## Channel 2. Differential Awareness During Promotional Campaign

- High-BJP-support district may feature greater media coverage
- Higher awareness may have led to greater adoption

**Support for BJP**




**Google Search Activity**

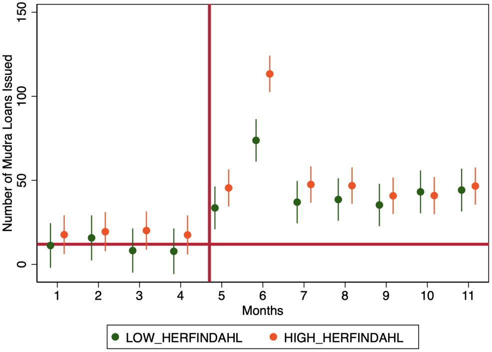



We confirm these results in formal multivariate regression tests

# Assessing Demand Channels-III

## Channel 3. Demand Mudra Loans to Support BJP

- Taking Mudra loans may carry the symbolic value of supporting BJP
- Focus on districts where BJP support between 45%-55%
- Use Herfindahl index to test degree to which districts are contested




We confirm these results in formal multivariate regression tests

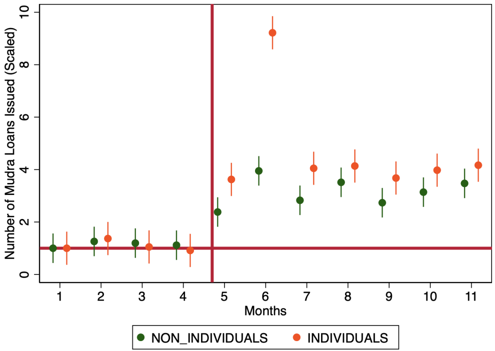
# Individuals vs. Businesses-I

Compared to businesses, individuals are

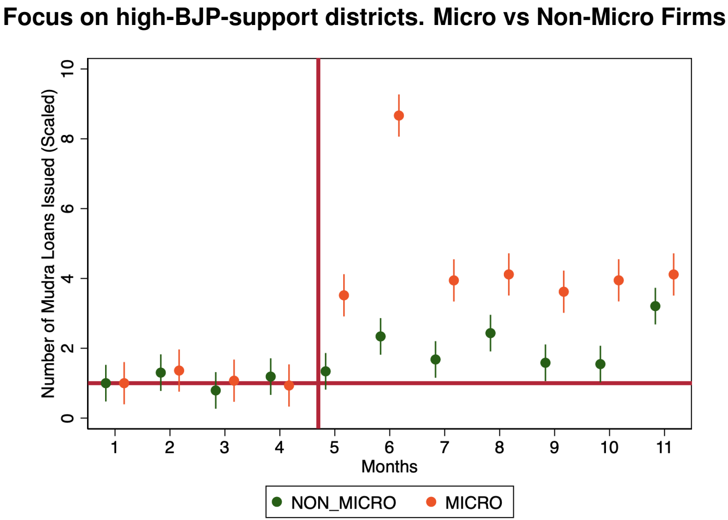
- less sophisticated
- make decisions alone rather than in groups

→ Political partisanship may play a bigger role in decisions

**Focus on high-BJP-support districts. Individuals vs Businesses**

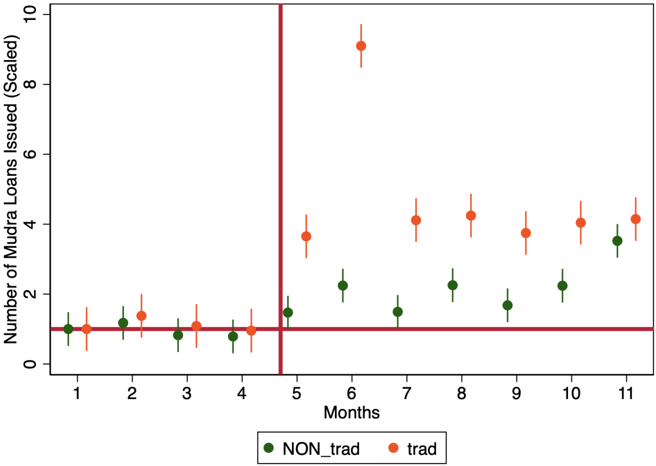


# Individuals vs. Businesses-II



# Individuals vs. Businesses-III

## Focus on high-BJP-support districts. Trade vs Non-Trade Firms



# Economic Magnitudes

In back-of-the-envelope calculations (many assumptions), we show:

- 10% of the Mudra loans were originated due to the campaign: \$3.9B

Given that ≈60% of the Mudra loans end up in default:

- \$2.2B transferred from taxpayers to participating Indian borrowers

# Conclusions

Main Findings:

- Partisanship affects the transmission of fiscal policies
- Effects are demand-driven rather than supply-driven
- Agents' sophistication interacts with partisanship
  (more sophisticated agents are less susceptible to it)
- Economic effects of partisanship are economically substantial