Political Partisanship and the Transmission of Fiscal Policy

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Abstract

We document that support for the ruling party ("partisanship") increases the take-up of government programs in which participation is costly. The take-up rates of a large-scale Indian loan-guarantee program, *Mudra loans*, diverge across low- and high-partisanship electoral districts but only months after the widely-advertised program's launch, once rulers relate take-up rates to party success. In loan-level administrative data, borrowers' risk, interest rates, subsequent default rates, and access to bank branches do not vary with partisanship. Regular-loan issuance, which captures the local demand and supply of credit, does not vary with partisanship either. The effects are larger in contested districts.

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Since the start of the twenty-first century, democracies have witnessed an increasingly partisan and polarized political discourse (Abramowitz and Saunders (2008), Fiorina and Abrams (2008), Gentzkow et al. (2011)), including a radicalization of rhetoric and language in traditional and social media. Higher representation of radical economic platforms in legislative and executive bodies is one route through which political partisanship has been shaping the effectiveness of fiscal policies.[1]

A more subtle route through which partisanship can shape policy effectiveness is agents' subjective beliefs about the benefits of participation (e.g., see Barrios and Hochberg (2020a); Cookson, Engelberg, and Mullins (2020); Dahl, Lu, and Mullins (2021); Engelberg, Guzman, Lu, and Mullins (2021)). In the same way in which partisanship shapes professional decision-makers' beliefs (Kempf et al. (2021); Kempf and Tsoutsoura (2021); Fos et al. (2022)), consumers' support for the party that implements the program might increase their subjective beliefs about the benefits of participation, especially for complex policies whose financial implications are hard to understand absent financial literacy (e.g., see D'Acunto et al. (2020), and D'Acunto et al. (2021)). Moreover, if program participation is portrayed as a way to support the ruling party, the effects of partisanship should be higher in contested districts—where other parties have strong support, too—because the value of showing support for one's preferred faction is higher when the faction's primacy is threatened (e.g., see Ali and Lin (2013), and Miller and Conover (2015)).[2]

In this paper, we study if and how fiscal-policy program uptake relates to partisanship. Tackling this question faces a major challenge: the econometrician needs to observe a setting in which the role of consumers' support for the ruling party can be disentangled from governments catering their policies to the needs of their supporters as well as from unobserved time invariant and time varying drivers of economic activity correlated with partisanship (D'Acunto et al. (2021)).

Our empirical setting is a large-scale government-guaranteed loan program in India (*Mudra Loans*), which launched in April 2015 and has been running since. Program take-up is costly in terms of both administrative set-up costs and financial interest.[3] This setting helps us disentangle

[1]See Prior (2013), Lelkes (2016), Bail et al. (2018), Boxell et al. (2017), Allcott et al. (2020), Cukierman and Tommasi (1998), Aghion et al. (2004), Alesina and Rosenthal (1989), among others

[2]For a discussion of the psychological channels through which voters might obtain value from showing support for their preferred party, see, for instance, Harder and Krosnick (2008).

[3]As we show below, the median Mudra loan in our nationally-representative sample is charged an APR of 25%, which is close to rates for commercial loans in India.

the role of partisanship from other drivers of program take-up because the program was broadly covered by traditional and social media since its launch but starting in October 2015, India's Prime Minister (PM) Modi engaged in a heavily personalized national promotion campaign that linked program take-up rates to the ruling party's political success. The time in which information about the program diffused to the public and the time in which program participation started to signify support for the ruling party differ in our setting. At the same time, potential unobserved time-invariant economic drivers of participation correlated with partisanship should affect participation rates similarly before and after the promotion campaign.

Figure 1: Mudra Loans per Capita Over Time by Support for the Ruling Party (BJP)

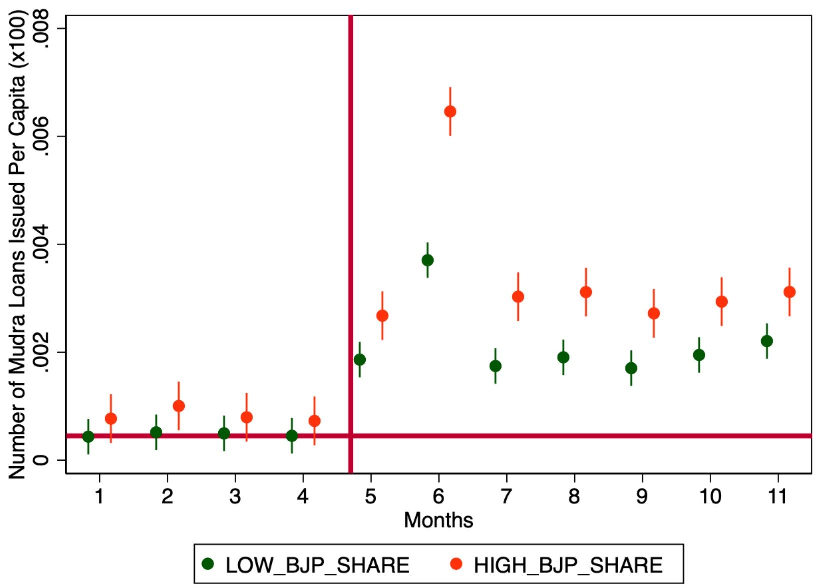

Figure 1 previews our baseline results. It is based on aggregating individual-level loan data from a leading Indian bank, which we describe in detail below. To construct this figure, we compute the total number of Mudra loans per capita issued in each Indian electoral district in each month since May 2015—the first month after the Mudra loan program was implemented and discussed in the media—and until March 2016. We compute the average of Mudra loans per capita across districts above and below the median based on the vote share of India's ruling party, the BJP, in the 2014 general elections, when the BJP rose to national power.[4]

Figure 1 reveals two raw-data facts that motivate the rest of our analysis. First, the number

[4]All patterns are similar if we compute averages weighed by districts' population or loan value.

of loans per capita issued across the two sets of districts did not differ economically or statistically after the program launch and before Mr. Modi's promotion campaign. Second, immediately after the campaign started (which we indicate with a vertical red line), program take-up increased substantially across all districts but economically and statistically more in districts with higher support for the ruling party. This divergence spikes in the immediacy of the campaign and remains economically and statistically large over time.

These baseline facts are robust features of the data: They hold in multivariate individual-level loan regressions, in which we find that the likelihood of loan issuance during and after the start of the promotion campaign is higher where BJP support is higher, even after controlling for borrower-level proxies for risk (interest rate, loan amount, and estimated probability of default) and the demographic characteristics we observe, which determine program eligibility. These results reduce the concern that time-varying economic shocks across electoral districts might explain the differential take-up rates. Moreover, we find that aggregate characteristics of the pool of potential borrowers across districts do not differ systematically based on BJP support. We find no differential take-up rates across rural and urban districts around the campaign. These results do not change if we only exploit variation within borrowers' size groups and industries.

After establishing the baseline reduced-form results, we investigate the underlying economic channels. First, we propose tests to determine whether the demand for loans, the supply, or both drive the results. An effect through the demand for loans is consistent with our opening motivation: When potential borrowers estimate the expected costs and benefits from participating in a (costly) government program for which they qualify, support for the ruling party might increase their expected benefits of participation (including due to the symbolic value of demonstrating their support for the party).

At the same time, the supply side might drive our results: Banks that are more connected to the ruling party might be laxer when originating Mudra loans—e.g., approve riskier borrowers and/or quote lower interest rates than appropriate given borrowers' risk— to contribute to the "success" of the program and obtain potential future benefits from the government (e.g., see Faccio (2006), and Faccio et al. (2006)).[5]

[5]As we discuss below, Mr. Modi and the BJP have been defining the program's success mainly in terms of the number

For a nationally diffused bank like the one whose loans we observe, a C-suite bank-level push to issue more Mudra loans would not affect districts differentially by ruling-party support unless the bank had more branches in high-BJP-support districts, which we dismiss directly in the data. Yet, within the same bank, origination quality might differ systematically across districts. For instance, Dagostino et al. (2020) show that bank officers' partisanship affects the characteristics of the loans they issue by shaping their economic beliefs. We find that average interest rates and the average likelihood of Mudra loan default up to 5 years after origination (the end of the time series in our data) do not differ by BJP support. In fact, the average default of loans issued during the promotion campaign is *lower* than that of loans issued before the campaign in both groups of districts. Loan officers in high-BJP-support districts thus did not start to dig deeper into the pool of potential borrowers after the promotion campaign relative to loan officers in other districts. If anything, high-quality borrowers who qualified for the program since its launch did not start demanding Mudra loans until when the promotion campaign related Mudra loan take-up to BJP's success. This pattern is consistent with the possibility that borrowers in high-BJP-support locations did not value such a form of financing more beneficial than its costs before the campaign but did so after the campaign.

We move on to further investigate the potential role of such a demand-side channel. First, under this channel, borrowers in high-BJP-support locations should not be more willing to demand other forms of financing after the promotion campaign because only Mudra loans' take-up was promoted by the ruling party. We can test this conjecture directly in our setting by studying the take-up of loans issued *outside* the Mudra program at the same time and in the same locations as Mudra loans. We find that non-Mudra loan issuance and characteristics do not differ across districts by BJP support, either before or after the promotion campaign. This test also corroborates that unobserved local business cycle shocks and their effects on the demand and supply of loans cannot drive our baseline results (e.g., see Breza (2019)).

Second, we ask whether political support for the BJP might increase potential borrowers' awareness of the Mudra loan program—for instance, because BJP supporters followed the promotion campaign more than others (see Prior (2013) but also Boxell et al. (2017)). We do not find support

of loans issued and rupee amounts disbursed through the program. Loans' default rates or other measures of performance, which are subject to a heated political debate, are barely discussed by government officials.

for this channel. To proxy for the role of information diffusion during the campaign, we consider the intensity of online searches for the term "Mudra" across space during the campaign period. Intuitively, if the campaign resonated more with borrowers in high-BJP-support areas, the intensity of the search for the program and the application process should be higher in high-BJP-support areas,[6] but we do not find any evidence of a positive or negative relation in the data. Consistently, when we re-estimate our baseline multivariate specifications adding the local intensity of searches as a covariate, we find that loan issuance was higher in areas with higher information search during the Modi campaign. And yet, the estimates of the coefficients attached to local BJP support stay virtually identical both economically and statistically.

We then consider that the promotion campaign could increase BJP voters' expected benefits of taking Mudra loans, because they might obtain value from supporting their party when they are called to action by its leaders. To test this channel, we would need variation in the value voters obtain from supporting the ruling party in our observational context. We propose comparing districts in which the level of BJP support is the same and close to the absolute majority, but the support for other parties varies; that is, districts that are more or less contested. The rationale for this test is that the value of showing support for the preferred faction is higher when the primacy of this faction is more likely to be threatened by stronger opposing forces (Miller and Conover (2015)).

The empirical design of this test is inspired by settings that exploit closely contested elections in the US (for instance, see Akey (2015) and Çolak et al. (2017)), although, unfortunately, the Indian multiparty system and the limited number of state-level elections do not allow us to obtain enough mass of electoral districts just above and just below the winning threshold to propose a regression-discontinuity strategy. Instead, we compare districts where the BJP had the same level of support, but the primary opposing coalition did not. We find that the association between the same level of BJP support and program take-up is higher in more contested districts, where the BJP and the main opposing coalition had close electoral results in the 2014 general elections.

Fourth, we further assess a potential role for subjective beliefs by investigating which types of borrowers drive our results. Mudra loans can be taken by individual or business borrowers. In the

[6] Unfortunately, we can only construct measures of online searches at the Indian state level rather than the electoral district level.

latter case, we observe business characteristics, such as size (number of employees), industry, and organizational form (sole proprietorship, partnership, or incorporated business). Like in the US and most other countries (Paravisini (2008), D'Acunto et al. (2018), Mullins et al. (2018), Bartlett III and Morse (2020), Barrot, Martin, Sauvagnat, and Vallee (2021)), all these categories are eligible for government-guaranteed loan programs. At the same time, whereas the financing decisions of an individual and sole proprietor are made by a single individual by construction, a committee composed of partners, shareholders, and/or professional management might discuss the pros and cons of financing choices in incorporated businesses. Appropriate due diligence in the assessment of the costs and benefits of participating in the Mudra loan program should be more likely in businesses, and especially in businesses managed professionally. And hence, the symbolic value of supporting the ruling party should barely enter the assessment of a professionally-managed business, whereas it should be more likely to play a role in choices made by individual borrowers and sole proprietors.

Based on these considerations, we focus on high-BJP-support districts (where we detect a larger increase in Mudra loan take-up since the start of the promotion campaign) and compare take-up across types of borrowers who make financing choices in the same high-BJP-support locations and at the same time. We find that the campaign-induced spike in Mudra loans is largely driven by individual borrowers. Among business borrowers, we only detect sizable effects for sole proprietors and micro firms (less than three employees).

In the last part of the paper, we discuss the economic relevance of our results, their external validity above and beyond the Indian setting, and the potential aggregate implications of political partisanship as a driver of the transmission of fiscal policy.

Beyond the contributions we have cited thus far, our paper relates to the empirical literature that studies the relation between fiscal policy and political partisanship. Existing work in this area mainly focuses on two aspects. First, the degree to which ruling parties use fiscal policy to increase their political support (e.g., see Manacorda et al. (2011), Levitt and Snyder Jr (1995), and Duchin and Hackney (2020)). Second, the extent to which ruling parties design and stratify fiscal policy interventions across demographic groups to target subpopulations whose electoral support they want to capture (Stokes (2005), Finan and Schechter (2012), Gonzalez-Ocantos et al. (2012)). Relative to these two broad areas, our work studies the reverse channel: whether consumers' pre-existing electoral support for the ruling party shapes their take-up of new government programs.

More broadly, our work relates to the literature that studies the origins and consequences of political partisanship and polarization. A large literature studies how information through traditional and social media affects beliefs (for instance, see Durante and Knight (2012), Barone, D'Acunto, and Narciso (2015), Allcott and Gentzkow (2017), Berinsky (2017), Campante et al. (2018), Nyhan et al. (2013), Taber and Lodge (2006), Barrios and Hochberg (2020b), Allcott et al. (2020)), the effects of media exposure on voting choices (DellaVigna and Kaplan (2007), Enikolopov, Petrova, and Zhuravskaya (2011), Gerber et al. (2011) Gerber and Green (2000), Durante et al. (2019)), as well as echo-chamber effects in ideological segregation and news consumption (Bakshy et al. (2015), Gentzkow and Shapiro (2011), Flaxman et al. (2016), Enikolopov, Makarin, and Petrova (2020)). In the context of political campaigns, Kendall, Nannicini, and Trebbi (2015) and Pons (2018) study the effects of political campaigns on voting behavior. We contribute to this literature by studying the effects of political partisanship and polarization made salient by politically-charged campaigns on choices involving real outcomes.

1 Institutional Setting: Mudra Loan Program and Political Campaign

As of 2015, micro, small, and medium enterprises (MSMEs) contributed to about 8% of the total GDP and 45% of the total manufacturing output of India. To incentivize dedicated investments by MSMEs, in April 2015 the Indian government launched a government-guaranteed unsecured-loan program called *Pradhan Mantri MUDRA Yojana* (PMMY), also known as the Mudra loan program.

The program's stated goal was to "fund the unfunded" by extending affordable credit to MSMEs that normally do not have access to the formal financial system. The overall objectives of Pradhan Mantri MUDRA Yojana (PMMY) were to register all the Microfinance Institutions (MFIs), regulate them, and assist them with financial and credit support in order to provide MSMEs with affordable credit. MSMEs in India often access credit outside the formal system due to lower bureaucracy and quicker approval times. For instance, in 2015, on the verge of the launch of PMMY, unorganized debt contributed to about one quarter of total debt in India. The Mudra loan program allowed MSMEs to borrow from all public sector banks, regional banks, private sector banks, foreign banks, and non-banking finance companies, which dramatically increased the proportion of organized debt in India.

PMMY was initially limited to MSMEs in non-farming sectors such as land transport, social and personal services, food, and textiles. As of April 2016, which is beyond the timing of our sample and analysis, the program was enlarged to include MSMEs engaged in agricultural activities such as horticulture and fisheries. In a second wave of enlargement of the program, PMMY added several sub-programs, such as Micro Credit Scheme (MCS), Refinance Scheme for Regional Rural Banks (RRBs) and Scheduled Co-operative Banks, Mahila Uddyami Yojna (Credit Scheme for Women Entrepreneurs), Business Loan for traders and shopkeepers, Missing Middle Credit Scheme (Credit scheme for MSMEs that are not funded by either banks or MFIs) and Equipment Finance for Micro Units. None of these components of the PMMY were in effect during our sample period.

Mudra loans are not backed by any form of collateral. Borrowers are not charged processing fees and can use the Mudra Loan program for a variety of purposes and loan forms, including term loans, overdraft facilities, or to apply for letters of credit and bank guarantees.

On the government-sector side, Mudra loans represent a standard form of loan guarantee in which borrowers' risk of default is shifted from the financial institution that originates the loan to the government budget. In exchange for providing this guarantee, PMMY aimed at reducing the informal debt system in India and increasing the ability of MSMEs to access the formal credit sector to finance the growth of their operations.

Our analysis is agnostic on the welfare consequences of this subsidized loan program. As we discuss in more detail when describing the data, the share of Mudra loans flagged as non-performing five years after origination is higher than 50%—an ex-post figure consistent with early-stage concerns raised about the program.[7] Assessing the welfare consequences of the effects of political partisanship on the program's size goes beyond our paper's scope because it would require us to define the

[7] A prominent example is Dr. Raghuram Rajan's discussion of the potential negative effects of the program on the stability of the Indian financial sector (see, e.g., India Today).

appropriate counterfactual for this policy. For instance, had the government decided to provide subsidies and direct transfers instead of guaranteeing Mudra loans, the costs of such alternative programs might have been larger than the costs of the Mudra loan program.

Moving on to the details of Mudra loans' design, while there is no minimum loan amount for Mudra loans, the maximum loan offered under the program is ₹1 million, which in April 2015 corresponded to about $16K. Depending on the amount borrowed, Mudra loans are classified as *Shishu* (under ₹50K), *Kishor* (between ₹50K and ₹500K), and *Tarun* (between ₹500K and ₹1 million). Mudra loans' maturity ranges between 3 and 5 years, and monthly installments can vary in size depending on the borrower's ability to repay. Interest rates assigned to borrowers are computed according to guidelines from the Indian central bank (RBI), based on the RBI definition of marginal cost of lending rate (MCLR).

1.1. Political Promotion Campaign in October 2015

At the time of its launch in April 2015, the parliamentary discussion, approval, and implementation of the *Mudra Loan* program were covered prominently by national and local media. Only several months later, the Indian government (Department of Financial Services) organized a media and physical political campaign over the period between September 27 and October 5, 2015, which involved the Prime Minister, Mr. Narendra Modi, and portrayed participation in the program as an act of support for the ruling party. Figure 2 shows a few examples of the advertisement material the campaign produced as well as several events covered heavily by traditional and social media, in which Mr. Modi took part to promote program participation.

This promotion campaign, which was heavily covered by national and local news sources, increased the salience of the *Mudra Loan* program as a measure of fiscal policy tightly connected to Mr. Modi and his BJP party. Indeed, the campaign received positive and negative coverage by media aligned with the BJP or opposing the BJP. Despite lasting for only one week, the campaign was pervasive in terms of its geographic outreach: events similar to political rallies were organized across 50 different locations of the country, and several BJP politicians and cabinet ministers participated. The one-week-long campaign was kick-started in the center of the country—Varanasi and

Uttar Pradesh—and moved to other locations in the following days. Each local event of the media campaign was coordinated centrally by the Department of Financial Services in cooperation with the State-Level Banking Committee (SLBC) of the state that hosted the event. As discussed below, states had to participate in the campaign organization irrespective of whether local governments were run by the BJP or opposition parties.

Overall, this promotion campaign is the event our analysis employs to compare the take-up rates of Mudra Loans before and after their connection to the BJP success became salient and across electoral districts in which the BJP had higher or lower support. In the aggregate, the promotion campaign appears to have been effective in increasing the take-up rates of the Mudra Loans program. Up until the campaign, from April to August 2015, approximately ₹8.7 Crore ($1.2 Million) were disbursed under PMMY. At the end of the semester (December 31, 2015), a total of ₹133,000 Crore ($18 Billion) were disbursed.

2 Data and Summary Statistics

Our core dataset is a 20% random sample of the loans issued by the largest public-sector bank in India over the 12 months between April 2015 and March 2016. The bank's branches are diffused throughout India, and the market share of its deposit is estimated to be about 25% of the whole country.

The fact that this is a public-sector bank raises concerns about whether our results are driven by the peculiar behavior of this bank relative to other financial institutions due to the campaign. We will dismiss this concern directly with a series of empirical tests in Section *4.1.*. Even before describing our data, though, we show that this concern has little scope. First, we collected official data on all the Mudra loans issued by each financial institution in India,[8] and we find that our bank originated only about 11% of all Mudra loans issued during our sample period despite accounting for about 25% of the total loan and deposit market in India. Our public-sector bank originated a *smaller* proportion of Mudra loans than its market share.

[8]We refer to the public data collected and published by MUDRA, the government-owned refinancing institution that runs and monitors the Mudra program.

Second, Figure 3 shows that our bank did not account for a higher share of Mudra loans originated in high-BJP-support areas, which would be a concern for our analysis. The x-axis sorts Indian states based on the BJP vote share in the 2014 general elections, which is measured on the left y-axis through the gray bars. On the right y-axis, we measure the share of all Mudra loans originated in each state in the 2015-2016 fiscal year that was issued by our bank (black diamonds).[9] Had we found that our bank issued a larger share of all Mudra loans in high-support states, and vice versa, we would have been worried that the loans we observed in our sample were biased towards higher issuance in high-support states. Instead, Figure 3 finds barely any relationship between the share of Mudra loans issued by our bank and the local BJP support. If anything, the bank has originated a relatively higher share of Mudra loans in a few low-support states, which suggests that our tests might exaggerate the extent of program take-up in some low-support states rather than the other way around.

Moving on to our data, the loan-level dataset includes information about the date of issuance, the loan amount, and the interest rate of each loan issued either under the Mudra program or at regular market conditions, which is crucial to design our falsification tests. Moreover, the dataset includes the categorization of the loan's performance (whether closed or still active) as of October 2020—the date we were provided the data. The performance categorization follows the official income recognition and asset classification (IRAC) norms by the Reserve Bank of India and is used to assess whether loans should be classified as "non-performing assets" (NPA) and written off by the bank.

Although we do not observe borrowers' identities, the loan-level dataset includes a set of borrower characteristics. First, we observe a borrower-type categorization, which consists of 32 types of borrowers, such as individuals, sole proprietor businesses, incorporated businesses, and other (less common) business legal forms. The data also contains information regarding the sector in which the borrower operates and, in particular, a set of categories within the manufacturing, trade, and services sectors. Finally, we observe some demographic information about borrowers: the geographic location at the level of PIN Code, which is a subdivision of cities similar to three-digit ZIP codes in the US; and the borrower's gender.

[9] We do not have information on total loans issued at the district level, but only aggregate state-level information on Mudra loans originated in each fiscal year collected by MUDRA.

The loan-level dataset also includes information about the supply side, that is, the identifier of the branch that originated the loan and the branch's PIN code.

To perform our analyses, we augment this core loan-level dataset with data we collect from public online sources. We obtain voting information and election results at the electoral district level for the lower House (*Lok Sabha*) from the Indian Ministry of the Interior. For each district, we observe the total number of electors, the total number of voters, and the number of votes obtained by each candidate on the ballot. For each candidate, we observe the political party they are affiliated with.

Note that the geo-locations of our datasets—PIN codes for the loan-level data and electoral districts for the voting data—do not fully map into each other. For this reason, we map PIN codes into electoral districts by assigning each PIN code to the voting district in which the PIN code's centroid lies.

2.1. Summary Statistics

Table 1 reports the summary statistics for the Mudra loans that are part of our loan-level sample. For each variable, we report the number of observations, mean, standard deviation, and salient percentiles of the variable's distribution.

Panel A focuses on loan characteristics and contains results for the loan amount, interest rate, loan performance, and the gender of the borrower. The average loan size is ₹123,470 ($1,700), but the distribution is somewhat skewed to the right, with smaller loans of ₹10,894 ($150) at the 5th percentile, ₹30,000 ($412) at the 25th percentile and a median loan of ₹50,000 ($687). At the top of the loan distribution (95th percentile), we find loans of ₹562,500 ($7,728). Interest rates average 9.8% per year, and the distribution is relatively compact: the 25th, 50th, and 75th percent of the distribution are 9.8, 11.25, and 12.3.

The variable "non-performing asset flag" equals one if the loan is delinquent five years after its issuance and zero otherwise. Delinquency on Mudra loans is very large—58% of all originated loans are delinquent five years after issuance. Finally, the female dummy shows that only 23.2% of the borrowers are female entrepreneurs. It is surprising we do not observe more women in the sample, given that one of the main reasons for women borrowing less than men in the literature has been attributed to them not having assets to put up as collateral, and MUDRA borrowers are not required to post collateral. This figure corroborates the relevance of non-wealth constraints hindering women's access to credit in India, which Naaraayanan (2019) documents.

Panel B of Table 1 focuses on the timing of loan origination. As mentioned in Section 1, the promotional campaign significantly impacted Mudra loan origination. We report the percentage of Mudra loans over the 2015-2016 fiscal year across three sub-periods. The first spans five months (May 2015-September 2015), the second the two months around the political campaign (October 2015-November 2015), and the third the four months after the campaign had ended (December 2015-March 2015). If Mudra loan issuance were uniformly distributed across the fiscal year, we would expect to observe (100/12*5)=41.66% of the loans in the first period, (100/12*2)=16.66% in the second, and (100/12*4)=33.33% in the third. Instead, we find that only 22.6% of the loans were issued before the promotion, 33.47% was issued during the promotion period, and 43.88% was issued post-promotion.

Panel C of Table 1 presents summary statistics for voting characteristics of the electoral districts in which Mudra loans are issued. We report the voting share of the BJP party, the voting share of the main opposition party—the Indian National Congress (INC)—and the Adjusted Herfindahl index of the voting share across all parties running for elections in each electoral district, which we will use as a measure of the extent to which an electoral district is contested between the BJP and the main opposition party, INC. The adjusted Herfindahl index is computed in two steps. In the first step, we compute, in each electoral district, $H_c^* = \sum_{i=1}^{N} v_{i,c}^2$, where $v_{i,c}$ is the vote share of the party in electoral district c. In the second step, we compute $H_c = \frac{(H_c^* - 1/N)}{1 - 1/N}$ for $N > 1$ and $H_c = 1$ for $N = 1$. The measure ranges from 0 to 1, going from least to most concentrated. The average vote share for the BJP across all districts is 45.04%, but we have a large amount of variation across districts, going from 9.7% at the 5th percentile to 64.9% at the 95th percentile. The share of the INC party is lower on average (26.7%) and also ranges widely from 1.79% to 45.25%. Concentration in political voting varies widely across political districts—it ranges from 21.96% at the 5th percentile to 45.34% at the 95th percentile.

Panel D of Table 1 reports statistics by categories of Mudra loans. The first variable is the percentage of small loans (*Shishu* loans), which comprise 98.48% of all loans. The second variable is a dummy that equals one for loans taken by individuals and zero for those taken by corporations. The majority of loans (87.49%) are taken by individuals. Finally, the program requires classifying loans by purpose at the time of origination: either trade & service or manufacturing. Most loans (94.20%) are issued to borrowers in the trade & services sector.

3 Political Support and Uptake of Guaranteed Loans

We start the description of our results by providing raw empirical evidence of the relation between political support and the take-up of Mudra loans in section *3.1.* and extend the analysis to multivariate regression specifications in section *3.2.*.

3.1. Raw Data and Motivational Evidence

We first consider the relationship between the take-up of Mudra loans and local support for the BJP party. We first consider the state level and compute the support for the BJP and the total number of Mudra loans issued each month. We then compute growth in loans issued in each state over the period October-December 2015, after the government's promotion campaign started, relative to the period June-August 2015. In Panel A of Figure 4, the x-axis reports the average support for the BJP, while the y-axis reports the differential growth in Mudra loans after the campaign relative to before.

Two facts are worth noting. First, all states experienced large increases in Mudra loan issuance after the campaign. Even Telangana, the state with the lowest growth, recorded a 100% increase in Mudra loan issuance. Second, the extent of issuance growth differed systematically based on BJP support: in states where the BJP obtained about 10% of votes, issuance grew by 150%, on average. At the other end of the spectrum, the average growth was approximately 250% for states in which BJP votes were about 60% of all cast votes.[10]

[10]Delhi is not reported in this specific plot but included in all the results reported in the paper. We report the plot that includes Delhi in Figure A.1.

The results computed at the state level allow visualizing geographic and political nuances in Mudra loan issuance but do not exploit the finest geographic variation in political support we observe. In Panel B of Figure 4, we repeat the analysis at the electoral district level. We report a binscatter plot including 50 bins, each of which summarizes about ten districts. We detect the same patterns as at the state level.

The results in Figure 4 use continuous cross-sectional variation in the support for the BJP but do not exploit the dynamics of Mudra loan issuance over time. To do this, we first compute the total number of loans issued each month in each electoral district. We then compute the average number of loans issued across electoral districts with low and high BJP support. We construct these two categories by dividing electoral districts (rather than the loan-level sample) into two groups of equal size based on the BJP vote share in the 2014 elections.

The results are reported in Panel A of Figure 5, where for each month and each group of districts, we report the average number of Mudra loans issued and the associated confidence interval. The vertical red line indicates the start of Mr. Modi's promotion campaign. Before the promotion started, low- and high-BJP districts had similar levels of Mudra loan activities. After the beginning of the promotion, the results diverge dramatically: the high-BJP-share districts jump from approximately ten Mudra loans per month to over 40 Mudra loans per month in September and 100 Mudra loans per month in October.[11] The change for low-BJP support districts is much less pronounced: the number of Mudra loans jumps from approximately ten before the promotion to 25 in September and less than 50 in October. Also, we find that the differential effect of the promotion campaign persists over time, as it is still present seven months after the campaign is over.

One of the potential concerns in Panel A of Figure 5 is that it averages the total number of loans across different districts. Even if districts are designed to include roughly the same number of voters, we repeat our analysis focusing on the total number of loans per capita and report them in Panel B of Figure 5. The results are qualitatively similar.

[11]We discuss in detail the economic magnitude of the effects in section 6 but recall that we observe a 20% random sample of the loans originated by the bank whose data we use, and this bank has issued about 11% of all Mudra loans nationally. If these proportions were homogeneous across all districts in the country, 100 loans in our sample would correspond to about 4,546 loans issued overall in that district-month observation.

3.2. Multivariate Analysis

To assess if the baseline patterns survive once we account for observed sources of variation that might correlate with support for the ruling party, we move on to multivariate specifications. We perform our multivariate analysis at two levels—the electoral-district and the individual-loan levels. The electoral district level allows us to study the variation in the number and value of loans across districts and over time, as discussed in the previous section, in a multivariate framework that absorbs systematic time-invariant characteristics across districts and the district-level time-varying observables we have. For this analysis, we estimate regression specifications of the following form:

$$\begin{aligned} Number/Value\ Loans_{j,t} = {} & \alpha_j + \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ & + \beta_2 \times BJP\ Share_j \times After\ Campaign_t + \gamma_1 \times During\ Campaign_t \\ & + \gamma_2 \times After\ Campaign_t + \delta \times BJP\ Share_j + X'_{j,t}\zeta + \epsilon_{j,t}, \end{aligned} \tag{1}$$

where $Number/Value\ Loans_{j,t}$ is the number of loans issued (columns (1)-(2)) or the aggregate value of Mudra lending (in millions of rupees, columns (3)-(4)) in district j and month t; α_j is a full set of district-level fixed effects; $BJP\ Share_j$ is the voting share for the BJP party in electoral district j in the 2014 Indian general elections; $During\ Campaign_t$ is equal to 1 for the months October and November 2015 and 0 otherwise, and $After\ Campaign_t$ is equal to 1 for after November 2015 and equal to zero before November 2015.

Table 2 reports the results, which confirm both qualitatively and quantitatively the facts we documented in the raw data when we partial out time-invariant district-level characteristics (including the level of support for the BJP) and control for time-varying characteristics of the borrower pool. These characteristics include the average interest rates charged in each district-month and the share of female borrowers over total borrowers in each district-month, which allows us to dismiss that systematic changes in the characteristics of the borrower pool after the campaign relative to before drive our results.

We also perform a loan-level analysis. The individual-loan level allows us to compare borrowers in the same district, all of whom had an economic motive to take a Mudra loan but took it at different points in time. It also allows us to partial out important loan-level proxies for risk and other individual-level characteristics. Moreover, this analysis allows us to control for any time-varying district-level business cycle shocks when we use individual-level proxies for BJP support rather than the district-level vote share.

For this analysis, we first construct a panel for each loan spanning April 2015-March 2016. The dependent variable is a dummy that equals 1 in the month the loan was issued and zero in all other months. We then estimate the following specification:

$$\begin{aligned} Loan\ Issued_{i,j,t} = \alpha &+ \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ &+ \beta_2 \times BJP\ Share_j \times After\ Campaign_t + \gamma_1 \times During\ Campaign_t \\ &+ \gamma_2 \times After\ Campaign_t + \delta \times BJP\ Share_j + X'_{j,t}\zeta + \epsilon_{i,j,t}, \end{aligned} \tag{2}$$

where $Loan\ Issued_{i,j,t}$ is an indicator variable equal to 1 if the loan i in electoral district j was issued on month t and 0 otherwise; and the other variables are defined as in Equation (1). The coefficients of interest are β_1 and β_2, which measure the differential Mudra loan issuance in the two months following the promotional campaign (β_1) and in the months after that (β_2), depending on the level of political support for the BJP party. We standardize the variable $BJP\ Share_j$ to have a unit standard deviation. Standard errors are double clustered at the electoral district and monthly date levels.

The results are reported in Table 3. Column (1) documents the higher issuance of Mudra loans in areas with higher BJP support during the political campaign. The association is statistically significant at the 1% level. Economically, the results suggest that a standard deviation higher BJP support is related to a higher probability of the Mudra loan being issued during the political campaign by 1 percentage point (pp). For comparison, note that the promotional campaign increased Mudra loans issuance by 12pp ($\hat{\gamma}_1$), so a standard deviation increase in BJP support relates to a higher probability of a Mudra loan being issued during the campaign months by $0.01/0.12 = 8.3\%$ at the 1% significance level. The $\hat{\beta}_2$ estimate is negative but statistically insignificant, suggesting that the political support effect on Mudra loan issuance declines after the two-month promotional campaign. The $\hat{\gamma}_2$ estimate is instead positive and statistically significant, suggesting that the promotional campaign overall had an impact several months after it took place. Economically, $\hat{\gamma}_2$ equals 7pp, which is 0.07/0.12=58% of the effect over the first two months after the campaign.

The second column adds loan-specific characteristics, such as interest rates and loan amounts, as additional covariates. It also absorbs other loan-level characteristics, such as the bank's assessment of the quality of the borrower (IRAC) and the size of the borrower's business (MSME). The coefficients of interest are virtually unchanged, both economically and statistically.

The third column adds the two borrower-specific characteristics we observe: gender and the type of organization based on the bank's 32 categories. Finally, the fourth column adds electoral district fixed effects, effectively controlling for static characteristics across electoral districts. In both cases, the estimates of interest $\hat{\beta}_1$ and $\hat{\beta}_2$ do not change.

3.3. Robustness

Because our results so far used an electoral-district-level variable as the proxy for ruling-party support—the local vote share of the BJP in the 2014 general elections—we are not able to fully exclude a role for district-level unobservables to explain our results, even though recall that such unobservables should explain the timing of the increase in Mudra loan take-up exactly when Modi's political campaign started. That is, most time-invariant district-level unobservables that might explain the take-up of the program in general would not be a relevant concern in our baseline multivariate results because their relationship with program take-up would hold in the same way both before and after the campaign.

Ideally, we would have an individual-level measure of the extent to which borrowers in our sample support the ruling party. Such a level of observation would allow us to assess our results when absorbing any time-varying district-level shocks that might explain the timing and willingness of local consumers to take up Mudra loans. Unfortunately, we do not observe such a measure in our data, and we were not able to set up a survey that reached out directly to the bank's clients due to privacy concerns.

In the absence of a direct measure of BJP support at the individual level, we propose one of the demographic variables we observe—borrowers' gender—as an imprecise proxy. This proxy is motivated by the fact that opinion polls in 2014, similar to those in other years, show that women are systematically less likely to support Mr. Modi and the BJP relative to men. For instance, in a set of editorial articles, political scientists Pradeep Chhibber and Rahul Verma have discussed the fact that, despite the appeal of Narendra Modi's figure to women, the BJP has not been able to revert women's historical lack of support for the party in the 2014 elections.[12]

An advantage of this proxy is that Modi's campaign has consistently emphasized the empowering of Indian women as one of Mudra's strategic goals (for instance, see Agarwala et al. (2022)). If anything, the systematic attempt to target women as borrowers during the political campaign represents a differential shock to the timing of loan take-up across genders in the *opposite* direction of what our conjecture, which is based on ex-ante BJP support, predicts. The main caveat of this proxy is that district-level time-varying shocks that changed the incentives of men and women to take up Mudra loans before and after the national Modi campaign differently might still explain our results. Even though such unobservables seem hard to envisage, except for the targeting of women that goes in the opposite direction of our effect, we cannot rule out this possibility formally.

In Table 4, we first estimate a version of equation (2) in which we replace the level and interactions of the district-level BJP vote share with a dummy variable for whether the borrower is a woman (column (1)). Women who take up a Mudra loan throughout our sample period are less likely than men to take it up during/after the Modi campaign, whereas they are relatively more likely to take it up before the campaign. In column (2), we add both sets of interactions in the same specification. The results for women are almost unchanged, and the results for the district-level BJP support survive—as expected, given that even if gender is correlated with BJP support, the variation in BJP vote share across districts captures many other determinants of BJP support above and beyond gender.

In column (3), we propose a specification that includes district-by-month fixed effects. This specification, which we cannot run in the baseline analysis due to the lack of variation of its interaction with the campaign dummies within districts and months, confirms the baseline results. Overall, we interpret this result as indicating that time-varying district-level shocks cannot explain the differential

[12]For instance, see "BJP has a gender problem" The Indian Express, available at: https://indianexpress.com/article/opinion/editorials/bjp-has-a-gender-problem/

timing of Mudra loan take-up by borrowers around the campaign between BJP supporters and other borrowers.

In columns (4)-(5) of Table 4, we propose a falsification test in which we compare the role of BJP support with the rural vs. urban residential location of borrowers. This test is motivated by the fact that the Mudra program had the increase of access to finance for rural borrowers as an objective. Hence, one might be concerned that the district-level BJP vote shares we use, in fact, proxy for the urban-rural composition of the population of borrowers if rural voters tended to support Modi and the BJP more than urban borrowers.[13]

Whether a borrower resides in a rural location does not predict the timing of Mudra loan take-up and especially does not predict a higher take up during the Modi campaign (column (4)). Moreover, once we add both interactions in the same specification (column (5)), the effect of BJP vote share at the district level stays similar to our baseline analysis. Finally, once we assess in column (6) the role of rural residence on the timing of loan take-up within districts-by-month—which we can, given that within each district we have both urban and rural borrowers—we detect no differential timing of take up for rural and urban borrowers.

4 Supply- vs. Demand-Side Channels

Our results so far are consistent with the BJP promotional campaign affecting the demand for Mudra loans, the supply, or both. This section considers these non-mutually exclusive channels and assesses their merit.

4.1. Supply of Loans

We start by considering a set of channels through which the supply-side of loans and banking, in general, might transmit the take up of Mudra loans differently across areas in which the electoral support for the ruling party differs (e.g., see D'Acunto and Rossi (2020)), before and after Mr. Modi's promotional campaign.

[13]Unfortunately, we only observe the rural/urban residence for a subset of borrowers for which the banks collected this information.

4.1.1 Access to Finance Across Space.

First, if bank branches were more diffused and accessible in districts that supported the BJP more in the 2014 general elections, and especially in more contested districts, even if the promotional campaign had the same effect on the demand for Mudra loans all over India, we would observe a higher incidence of issued loans where BJP support was higher. In our setting—a developing country in which access to finance varies dramatically across space (e.g., see Duflo and Banerjee (2011); Crouzet, Gupta, and Mezzanotti (ming); D'Acunto, Ghosh, Jain, and Rossi (2021); and Naaraayanan (2020), among many others), this possibility is not implausible ex-ante. We can assess this channel directly in our data because we know the locations of all bank branches of the bank whose loans we observe. To this end, we estimate electoral-district-level regressions (N=386) of the number of bank branches per capita on the BJP vote share and find that the coefficient is economically small and statistically insignificant: An additional percentage point in BJP vote share is associated with a 0.3% higher number of bank branches per capita relative to the mean (p-value=0.62). Adding any combination of the district-level observables we used in the previous analysis reduces the size of the estimated coefficient. Overall, we fail to detect differences in the bank branch structure across districts that might explain our results.

4.1.2 Political Support by Loan Officers/Bank.

A second potential supply-side channel relates to the political preferences of bank officers and local branch directors. We do not observe the political preferences of these agents directly. Still, it seems plausible to expect that, on average, loan officers and branch directions share similar political preferences as other local voters. In this case, once the campaign started, local bank officers in high-BJP-support districts might have wanted to issue more loans than others because of their own support for the BJP and hence might have employed laxer credit standards relative to bank officers in other districts (Keys, Mukherjee, Seru, and Vig (2010)).

This supply-side channel is compelling in our context because the bank whose loans we observe, as discussed above, is a large public sector bank and hence might attract bank officers who share the political views of the ruling party. Moreover, the administration and Indian media have been proposing the number and value of loans issued through the program as a measure of the program's success rather than assessing, for instance, the default rates or non-performing status of the originated loans.[14] It is also possible that the bank officers of our bank had a specific mandate to ensure the success of the Mudra loan program above and beyond their personal political preferences. Still, in this case, officers of *all* branches throughout the country would put a high effort into recruiting borrowers. Hence, we should not observe differential take-up rates across space unless the spatial variation in the political preferences of local borrowers mattered.[15]

To assess whether local bank officers in high-BJP-support districts employed laxer standards when issuing Mudra loans, we study the likelihood of default and of the non-performing status of the loans originated across space and over time. This supply-side channel would help explain our results if the sharp increase of loan originations in high-support districts after the campaign started corresponded to a higher share of defaulted or non-performing loans over time.

We do not find any evidence of such a pattern in Figure 6, which plots the share of non-performing loans up to five years after origination within each issuance month vintage.[16] If anything, the loans originated in the first two months of the media campaign are *less* likely to default relative to other loans, even if this difference disappears in subsequent vintages.[17] Crucially, this pattern, which is already inconsistent with laxer standards to begin with, does not differ across districts based on the level of BJP support.

We verify these results in multivariate specifications that follow the same structure as in Table 3 but use the non-performing status of the loan as of October 2020 as the dependent variable. The results are reported in Table 5. Overall, we do not find evidence consistent with a supply-side channel for the effects of local political support for the ruling party on the take-up rates of the government

[14]The emphasis on the number of loans originated is exemplified by the following statement from the Minister of State (IC) for Labor and Employment Santosh Kumar Gangwar to the Parliament of India (*Lok Sabha*) regarding his assessment of the success of the Mudra program: "*Under the Pradhan Mantri Mudra Yojana (PMMY), 20.84 crore loan accounts totaling an amount of ₹10.24 trillion have been sanctioned up to November 1, 2019.*"

[15]Moreover, as we show in section 6, our public sector bank issued about 11% of all Mudra loans in India during our sample period despite having a market share of about 25% of all deposits in the country. Even though the possibility that this bank acted as an "armed branch" of the government to issue Mudra loans might seem appealing (and has been proposed in the Indian political discourse), the data suggest no obvious evidence that this possibility might be true.

[16]Note that the confidence intervals shrink after the promotional campaign because the increased number of loans allows us greater precision in estimating the average default rates.

[17]Note that the average share of defaults of Mudra loans is substantial. Our statement here is about the relative performance of Mudra loans originated at different points in time and across voting districts and not about the overall average performance of Mudra loans.

program.

4.1.3 Pressure to Take up/Issue Mudra Loans by BJP-run Local Governments.

We also consider the possibility of a supply-side shock due to local governments rather than financial institutions. Specifically, states governed by the BJP and its allies might have implemented campaigns and/or provided additional incentives to convince locals to take Mudra loans and local branches to issue Mudra loans at the same time as Mr. Modi engaged in the national promotion campaign. Although we are not aware of any evidence supporting this potential role of local governments, Indian states have regularly been praised or attacked by Mr. Modi and high-level government officials based on the number and amounts of Mudra loans issued.

To assess this channel, in Table 6, we repeat our baseline analysis separately for loans originated in states whose local assemblies and rulers are from the BJP or allied parties (odd columns) and from other parties, including the Indian National Congress (INC), its allies, as well as third parties (even columns). Under the supply-side channel we are considering, we should observe higher effects in BJP-run states.

In columns (1)-(2), we repeat the analysis in column (1) of Table 2. We find that the size of the estimated coefficients is quite similar across groups of states, and we cannot reject the null that any of the corresponding coefficients are the same at standard levels of significance. If anything, the difference in the coefficients attached to the time dummies goes in *opposite* direction during and after the campaign. In columns (3)-(4), we estimate the restrictive specification of column (4) of Table 2 and again find similar results across the two groups of states.[18]

4.2. Demand for Loans

We move on to consider a set of non-mutually exclusive demand-side channels that might explain our baseline results.

[18]Note that we miss information on demographic controls and loan-level characteristics disproportionally more for BJP-ruled states, which is why the proportion between the sample sizes switches between columns (1)-(2) and columns (3)-(4). If we estimate both specifications on the subsamples of columns (3)-(4), the results are virtually unchanged.

4.2.1 Unobserved Shocks to the Demand for Loans.

Unobserved shocks to the demand for credit, irrespective of the Mudra program, might have hit electoral districts differently at the same time as the promotion campaign that linked Mudra-loan take-up rates to the BJP's success. A pure coincidence of the two timings seems implausible. Still, a reverse-causality argument is plausible: Mr. Modi might have decided to promote the program precisely when the demand for loans was expected to increase in India and especially in the voting districts that supported his party.

To assess a potential role for unrelated unobserved demand shocks, we design a falsification test that exploits an institutional feature of the Mudra loan program—the fact that issued loans can qualify for the Mudra program only if the amount does not exceed ₹10 lakhs (i.e., ₹1 million). In the presence of unrelated unobserved shocks to the demand for credit in October 2015, we would expect that the demand for loans below the Mudra cap and the demand for larger loans would increase similarly. Because of the incentives created by the Mudra program, these shocks might have induced the bunching of borrowers at the cap value for those who needed amounts slightly larger than ₹10 lakhs. Even in this case, under unobserved demand shocks, we should still detect an increase in the demand for loans that are large enough to make the incentives to bunch at the cap irrelevant (D'Acunto and Rossi (2020)). By contrast, if no local unobserved and localized shocks happened around October 2015, we should observe no differential patterns in the origination of loans above the ₹10 lakhs threshold.

Our results appear inconsistent with the possibility of unobserved shocks to demand across space and over time as an explanation for the results because we find that the issuance of loans above the ₹10 lakhs threshold did not increase around October 2015, and it was not different across districts with different levels of BJP support. We report these patterns in Figure 7, which replicates our baseline raw-data results but for the sample of loans above the Mudra-cap threshold.[19]

4.2.2 Varying Program Awareness During the Promotion Campaign.

The promotion campaign might have increased awareness of the Mudra loan program

[19]Note that non-Mudra loans, which are substantially larger than Mudra loans on average, are issued less frequently, as highlighted by the figure.

differentially across space based on local BJP support. This possibility does not conflict with our proposed interpretation that political partisanship increases agents' willingness to take up governmental programs. It suggests, though, a specific channel whereby this higher take up derives from the fact that households who support the BJP are more likely to attend to and absorb news and information provided by the BJP more than other households.

Before performing a formal test, we note that at least two facts seem barely consistent with this channel. First, the Mudra loan program had been covered extensively by national and local media since its approval at the end of April 2015 and well before the promotion campaign (October 2015). Potential borrowers throughout the country had several months to learn about this program from standard media sources as well as through information diffusion among peers before the campaign.

Second, we find that the gathering of information about the Mudra loan program during the promotion campaign was higher in areas where BJP support was lower. Figure 8 shows this fact graphically by comparing the state-level variation of BJP support in the 2014 elections (left panel) with the extent of Google searches for the term "Mudra" during the two weeks of the promotion campaign (right panel).[20] In both panels, the darker a state, the higher the value of the variable in that state. We can see that the states where BJP support was higher in 2014 are not those in which gathering information about the Mudra program was higher during the campaign and vice versa. Had the promotion campaign raised BJP-supportive borrowers' interest in gathering information about the program more, we would have expected positively correlated spatial patterns across the two panels of Figure 8.

We assess if awareness of the program and higher take up due to political support are indeed separate channels in Table A.1 of the online appendix. Here, we replicate the results of Table 3 but add the level of Google SVI intensity and its interaction with the dummies that identify the campaign and the subsequent periods. If BJP support did not act through awareness of the program, we would expect our baseline effect not to be affected by adding these proxies for information gathering. At the same time, higher information gathering should be related to a higher propensity to take up

[20]Specifically, we report the average Google search volume index (SVI) across Indian states from September 20, 2015, to October 24, 2015. In each state, Google computes the average daily ratio of searches for the term "Mudra" relative to all other Google searches in the state. Google then ranks these ratios across states and attributes a higher Google SVI to the states higher in the ranking and vice versa.

Mudra loans as a separate channel if our proxy for program information search and awareness was meaningful.

Table A.1 confirms both conjectures. On the one hand, the size and significance of our baseline results do not change in the new specifications. On the other hand, borrowers in areas with a higher intensity of gathering information about the Mudra loan program during the promotion campaign tended to take up more loans during and after the campaign relative to borrowers in other locations, ceteris paribus, which corroborates that our proxy for (endogenous) interest in gathering information about the program does correlate with higher program take-up rates.

4.2.3 The Value of Participation to Partisans: Evidence from Contested Districts.

Another demand-side channel through which BJP support could shape beliefs about program participation and hence explain the differential dynamics of take-up during and after the campaign relative to before is the symbolic value of participating for BJP supporters. Similar to casting a vote for the BJP, supporters could attach a positive value to participating in the program once the government emphasizes that higher take-up rates are to be interpreted as a sign of success of the BJP.

To obtain variation in the symbolic value of participating in the program for BJP supporters, we consider that the symbolic value of showing support for the preferred political party is higher in contexts in which the primacy of this party is more likely to be threatened by stronger opposing forces (Miller and Conover (2015)). We, therefore, ask whether, keeping constant the level of support for the BJP, the effects we have documented so far are stronger in electoral districts in which the BJP faces a stronger opposing coalition, and hence the BJP's primacy is threatened significantly by such coalition.

For this exercise, we limit the analysis to districts in which the BJP has a level of support close to the absolute majority from above or below—a vote share between 45% and 55%. Across these districts, the BJP has approximately the same level of support. Still, the value of showing support for the party is likely to vary based on whether the BJP faces a strong opposition, which might threaten its status as the strongest party. We compute the adjusted Herfindahl index of all parties' vote shares for the 2014 general elections in each district as described in Section *2.1.*.

We first report the results graphically in Figure 9, in which we divide the subset of districts with a similar level of support for the BJP (around the absolute majority) into two groups—low- and high-Herfindahl districts. The figure shows that the increase in Mudra loan issuance is higher in more contested districts among districts whose support for the BJP is similar. The plot, though, seems to suggest that the difference between low- and high-Herfindahl constituencies fades a few months after the promotion campaign, whereas, in the raw data, the baseline association between the level of BJP support and program take-up stayed rather unchanged over time.

We move on to estimate the following multivariate specifications at the individual-loan level:

$$\begin{aligned}
Loan\ Issued_{i,j,t} = \alpha &+ \beta_1 \times BJP\ Share_j \times Polarization_j \times During\ Campaign_t \\
&+ \beta_2 \times BJP\ Share_j \times Polarization_j \times After\ Campaign_t \\
&+ \gamma_1 \times BJP\ Share_j \times During\ Campaign_t + \gamma_2 \times BJP\ Share_j \times After\ Campaign_t \\
&+ \delta_1 \times Polarization_j \times During\ Campaign_t + \delta_2 \times Polarization_j \times After\ Campaign_t \\
&+ \theta_1 \times During\ Campaign_t + \theta_2 \times After\ Campaign_t \\
&+ \zeta \times BJP\ Share_j + \xi \times Polarization_j + \epsilon_{i,j,t}, \qquad (3)
\end{aligned}$$

where all variables are defined in Equation (2), except for $Polarization_j$, which is the normalized Herfindhal Index as described above.

In the first column of Table 7, The estimate of β_1 is positive and significant, indicating that the baseline higher likelihood of loan uptake during the political campaign in high-BJP-support districts (captured by $\hat{\gamma}_1$) is even higher in more contested districts.[21] The estimates of θ_1 and θ_2 confirm that, within similar-BJP-support districts, like in the full sample, loan issuance increased not only during but also after the campaign. The estimated $\hat{\zeta}$ suggests that, on this restricted sample, the probability of issuing Mudra loans outside of the promotion period is lower for constituencies with high BJP support, dismissing the concern that areas with higher BJP support are also the ones that have a higher endogenous demand for Mudra loans. Finally, note that the estimate of β_2 is insignificant, confirming the evidence in Figure 9 that the differential impact of the promotion campaign in contested districts is short-lived.

[21] Note that the variation in BJP support is substantially lower in this sample, in which we only focus on districts where the BJP vote share is between 45% and 55%.

The results in columns (2)-(4) of Table 7 add the same controls and absorb the same quantities as in Table 3. In all cases, the coefficient estimates do not vary noticeably.

5 Heterogeneous Effects: Individual vs. Business Borrowers

If our baseline results are driven by borrowers' beliefs about the value of program participation, when comparing individual and business borrowers we would expect that individual borrowers drive the results for at least two reasons. First, individual borrowers are likely to be less sophisticated in financial decision-making than business borrowers (Simon (1979)), which would lead them to rely more on information unrelated to the actual viability of the program when assessing the value of participation. Second, by construction, individual borrowers make decisions alone, and hence any idiosyncratic determinant of their beliefs about the viability of program participation influences their choice. By contrast, for business borrowers, and especially those incorporated and those run by professional management, financing choices are likely to be vetted by a team, which might reduce the effect of idiosyncratic shocks on the beliefs of any individual team member.

We first compare the effects across individual borrowers—consumers or small business owners—and incorporated borrowers. In the top panel of Figure 10, we focus on electoral districts with high-BJP shares and split the sample into individual and corporate (non-individual) borrowers. To make the results comparable across the two groups, we standardize the borrowing in April 2015 to be equal to 1. We can see that borrowing before the promotion campaign behaved identically for individual and corporate borrowers. Right after the campaign, instead, the take-up of Mudra loans by individual borrowers increased more rapidly and reached a peak increase of 1,200% in November 2015. The borrowing of incorporated firms increased at substantially lower growth rates.

Note that when we focus on lending around the campaign, we are comparing borrowers in the *same* (high-support) districts, and hence that were facing the same local business cycle shocks. These results thus also corroborate our earlier tests that dismiss a role for potential unobserved local business cycle shocks, which would be faced similarly by individuals and incorporated firms within the same districts.

The heterogeneity across types of borrowers also supports our interpretation that local borrowers' higher take-up rate of Mudra loans is due to political support for the ruling party. We propose two arguments for why political support should be more relevant for the demand for loans from individual agents rather than the demand from incorporated firms. First, individual agents are, by definition, singleton decision-makers. Incorporated firms, instead, are likely to include a committee of agents that contribute to the elaboration of financing decisions, which might consist of the firm owner and the main executive decision-makers, such as other shareholders and other executives. Unless all the decision-makers that are part of such committees support the BJP, non-supporters might counteract the position of supporters by providing arguments for why taking up Mudra loans might not be advantageous for the firm. Moreover, a large body of literature in financial decision-making shows that, across disparate contexts, non-expert decision-makers are more subject to using rules of thumb or dimensions unrelated to the financial decision problem at stake when making choices (e.g., see Benartzi and Thaler (2001), Thaler and Sunstein (2009), Agarwal et al. (2009), Stango and Zinman (2009), and Nofsinger (2017)). That individual agents and small business owners have lower experience and ability in financial decision-making than the executives of an incorporated business, who make financial decisions regularly, seems plausible.

The second heterogeneity dimension we consider is borrower size within the group of business borrowers. In the middle panel of Figure 10, we repeat the baseline exercise separately for micro and non-micro firms in districts with high BJP support.

Micro firms include sole proprietorships and generally represent small business undertakings such as small stands selling widgets or produce. Non-micro firms instead represent companies with multiple employees and have a more structured organization. This categorization aims to repeat the comparison between single/small decision-makers and large decision-makers but within the group of business borrowers.

The middle panel of Figure 10 shows that micro firms in high-BJP-support districts increase their demand for Mudra loans by substantially more than non-micro firms after the promotion campaign. The effect is so pronounced and persistent that, even at the $7th$ month, we do observe significant differences in lending among micro and non-micro firms. Note that even though non-micro firms are by construction more likely to take larger loans relative to micro firms, the cap for loans to fall under the Mudra program is high enough to make these loans equally appealing to all firms, irrespective of their size.

Finally, we consider heterogeneity across businesses based on whether they operate in trade or manufacturing. Trade and services businesses tend to be smaller, often family owned and run, and often without any employees except for the owner. Instead, manufacturing businesses require locations of production and employees that engage in manufacturing activities. We see that the majority of the increase in Mudra-loan take-up by businesses in high-BJP-support districts arises among trade and service businesses rather than manufacturing firms (see the bottom panel of Figure 10).

6 Quantifying the Aggregate Effects of Political Support on Policy Uptake and Costs

This last section aims to discuss a complex question that has policy implications—can we think about a way, perhaps even under strong assumptions, to provide an assessment of the *aggregate* effects of political partisanship on the transmission of fiscal policy programs whose participation is costly?

Several caveats exclude a simple answer to this question. First, estimating the size of one specific channel on policy uptake requires stronger assumptions than documenting the existence of such channel in the data and dismissing other potential explanations. The second challenge is that our sample only includes a fraction of the Mudra loans originated by the bank that provided us with the data, which in turn is only one of the several banks and financial institutions, including many micro-credit institutions that are diffused in India, that have been originating Mudra loans since the program started.

In an attempt to tackle the first challenge, we run our analysis at the level of electoral districts—the level at which we measure BJP support. We propose to bound the effect of channels unrelated to political support by computing the change in the uptake of Mudra loans per capita in the electoral district in our sample for which the BJP voting share is lowest.[22] Intuitively, BJP support should have barely any role in aggregate uptake in such a district because the share of the local population that supports the BJP is negligible. Changes in uptake around the campaign in that district should thus be driven by characteristics other than partisanship. The major caveat of this procedure is that it assumes all the channels unrelated to partisanship are fully active in that district, and their effect around the time of the campaign is captured fully by the change in uptake in that specific district. If we believe that some channels driving uptake might not be active in the district in which BJP support is low but might be active in other districts, this procedure would estimate an upper bound of the aggregate effect of partisanship on the uptake of the Mudra loan program.

To tackle the second challenge, we propose extrapolating the originating behavior of the loan sample we observe to the aggregate origination of Mudra loans within our bank and across financial institutions. Extrapolating within the bank seems rather innocuous—our data are a 20% random sample of all the Mudra loans the bank issues, without any form of stratification or restrictions. We have no compelling reason to be concerned that the remaining (unobserved) loans the bank issues have systematically different determinants and dynamics around the campaign. Extrapolating from our bank to other financial institutions is more concerning because it assumes that our bank's reaction and other banks' reactions to the political campaign are the same. This concern is limited by the evidence in Figure 3, where we fail to detect a relevant role for the originating behavior of our bank in the staggered uptake of loans across districts sorted by BJP support. There, if anything, we find that our bank, which is owned by the government, reacted less to the promotion campaign relative to other banks.

Armed with these caveats, we proceed to our baseline estimation of the aggregate effects of political support on policy uptake as follows. First, we compute the difference in the number and rupee-value of Mudra loans issued per capita (number of electors) before and after the start of the campaign in the district with the lowest BJP vote share in the 2014 general elections—the *Anantnag* district in the state of *Jammu & Kashmir*, in which the BJP obtained only 1.26% of the local vote.

[22] Our results do not change if we consider the average change in uptake across a group of voting districts at the bottom of the BJP-vote-share distribution to account for the concern that the lowest-support district is an outlier.

We then compute the change of the average per-capita loan take-up rate before and after the campaign similarly for all the other districts and subtract the Anantnag change. We interpret the change in lending within districts above and beyond the change in Anantnag as the increase in Mudra lending due to the campaign after purging from other potential national shocks that occurred in the same month as the campaign (October 2015). The top panel of Figure A.2 in the Online Appendix reports a binscatter plot of these estimated per capita changes against districts' BJP vote shares in 2014. Consistent with the baseline results in the loan-level analysis of the paper, the relationship between this estimated purged change and the BJP vote share at the district level is positive.

In a third step, for each district we multiply the purged per capita change by the number of electors in the district to obtain values in level for the number and value of loans issued. The bottom panel of Figure A.2 in the Online Appendix reports the levels of the estimated number of Mudra loans originated in each Indian district due to the campaign, as computed based on the steps above.

We then sum up the values across all districts. Finally, in the last step, we impose the assumption that the whole supply side of finance behaved similarly to the bank whose data we observe, which allows us to aggregate the effects up to the level of the whole Indian economy. Because we observe a random sample of 20% of loans originated by our bank, we first divide the changes by 20%, which allows us to aggregate up to the overall lending of our bank. Then, we divide again by 11% because our bank's market share of Mudra loans is 11%.

Based on these steps, we estimate that, over the time period we consider (between May 2015 and March 2016), 3.36 million Mudra loans were originated in India due to the promotion campaign. This figure represents about 10% of the total amount of Mudra loans originated by any financial institutions during the same period. In terms of rupee value, we estimate that the loans originated because of the campaign amount to about 247 billion rupees, i.e., about $3.9 billion.[23]

The last dimension we attempt to quantify is the aggregate cost of the campaign-induced higher take-up of Mudra loans to the taxpayer. On top of all the caveats discussed above, tackling this question raises the additional issue of what economic transactions should be considered as costs to taxpayers. One possible definition is that the policy has no cost for the taxpayer if it is budget

[23]This figure is based on the average daily rupee-dollar exchange rate in September 2015.

neutral, that is, if all the loans that are issued under the program are repaid in full, including interest, by their maturity. This definition implies that we can estimate the cost of the additional loans originated because of political support and the media campaign as the aggregate rupee value of the loans issued due to the campaign that defaulted and were not paid back.

Note that this accounting definition, which we use for our quantification exercise, is silent about the alternative options the fiscal policy authority faced, which would be crucial to consider if our aim was to provide program assessment or policy recommendations. For instance, if an alternative to the government loan program was to distribute the same amount of resources to Indians in the form of subsidies, such as universal income or other types of transfers, the Mudra loan program might have generated resources for the government's balance sheet as long as the interest repayments of those who repaid their loans were higher than the (potential) increase in sales tax and corporate tax revenues deriving from higher purchases by households who spent their universal income subsidies. Using our definition to assess the costs of the campaign to the taxpayer, thus, has no implications in terms of a normative assessment of the viability of the Mudra loan program.

Armed with these caveats, we find that about 57% of the Mudra loans originated during the campaign relative to before and relative to the electoral district with the lowest BJP support in 2014 were delinquent. Delinquency means that the loan was non-performing, recognized as such by the bank based on Indian (IRB) regulation, even in case the loan was not yet declared defaulted and fully written off by the bank at the time we obtained the data (i.e., October 2020). This figure about delinquent loans is in line with the rates of delinquency of Mudra loans throughout the program's life (see Shahid and Irshad (2016)). Based on this figure, we estimate that about 141 billion rupees (about $2.2 billion) were transferred to participating Indian borrowers through the Mudra program due to the impact of the campaign and were not fully paid back after issuance.

7 Conclusions

We argue that voters' support for the ruling party ("partisanship") shapes the transmission of fiscal policy by enhancing the take-up of programs in which participation is costly, especially in locations where the primacy of the ruling party is more contested. We document these facts in a setting in which characteristics of the demand and supply of credit do not differ across space based on partisanship: the credit risk of borrower pools, the interest rates charged, the subsequent default rates, and access to bank branches are similar in our laboratory in the field. Moreover, issuance of regular commercial loans during the time in which the program is active do not differ by partisanship either. This test helps us dismissing the possibility that systematic time-varying differences and local shocks that might have affected the demand or supply of credit differently across electoral districts might explain our results.

Our results open several questions for future research. First, a deeper understanding of the channels through which partisanship increases costly participation in government programs requires observing individual preferences, beliefs, and motivations. Designing large-scale surveys and survey experiments that vary the salience of various channels through which party support might affect consumers' beliefs about the benefits of program participation is a promising direction to tackle this question. Moreover, understanding the role of partisanship on program take-up over the business cycle has important policy implications, because governments typically aim to enhance the take-up of programs in times of economic crisis and low economic activity to spur aggregate demand and foster economic growth. Our setting has the advantage that the government program was implemented in a time of stable economic conditions, and the promotion campaign by the government was unrelated to business cycle considerations but rather aimed to increase program participation to enhance the ruling party's visibility and credibility, but future research should assess if levering on partisanship can be a low-cost channel of transmission of fiscal policy in times of economic downturn.

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Mudra Loan Promotion Campaign by Indian Prime Minister Modi

Figure 2. This figure shows examples of the advertisements and events covered by TV, other traditional media, and social media in which Mr. Modi participated during the political campaign to support participation in the Mudra loan program in October 2015.

Did Our Bank Lend More than Others in High-BJP-support States?

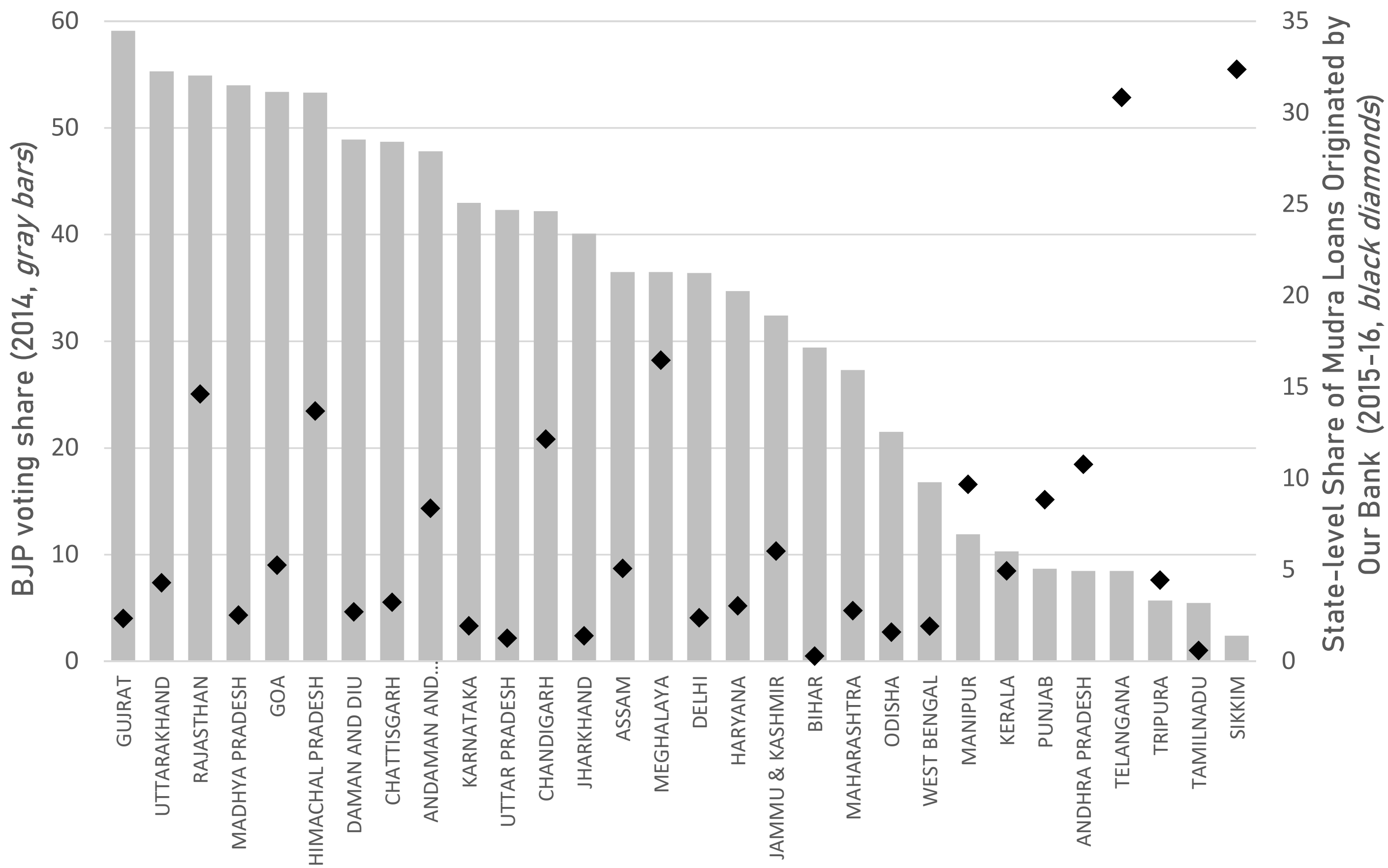


Figure 3. This figure sorts Indian states based on the BJP vote share in the 2014 general elections (left y-axis, gray bars) and reports the share of Mudra loans originated in each state in the fiscal year 2015-2016 that were issued by the bank from which we observe loan-level data (right y-axis, black diamonds).

Increase in Mudra Loans Origination During Promotion Campaign by Partisanship: States and Electoral Districts

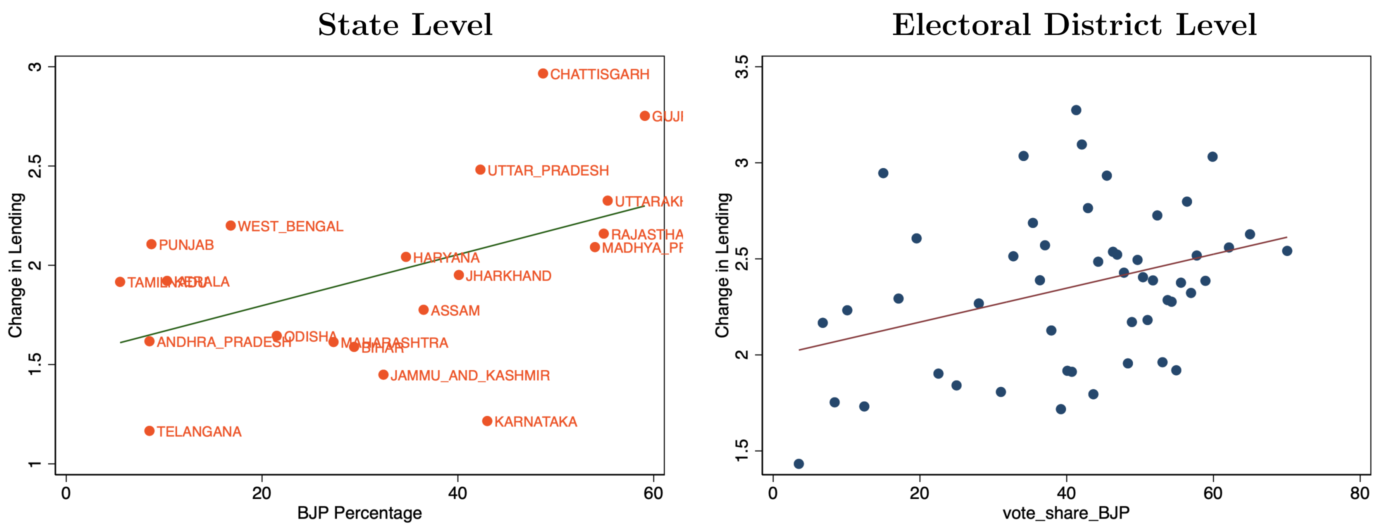


Figure 4. This figure relates the take-up of Mudra loans to BJP support across states and electoral districts. In Panel A, we first compute, at the state level, BJP support as the average BJP vote share in the 2014 general elections, as well as the total number of Mudra loans issued each month. We then compute the growth of loans issued in each state over the period October-December 2015, after the Mudra Loan promotion campaign started, relative to the period June-August 2015. The x-axis sorts locations by BJP support, while the y-axis reports the differential growth of Mudra loans after the campaign relative to before. In Panel B, we repeat the analysis at the electoral district level in a binned scatter plot.

Mudra Loans Origination by Partisanship

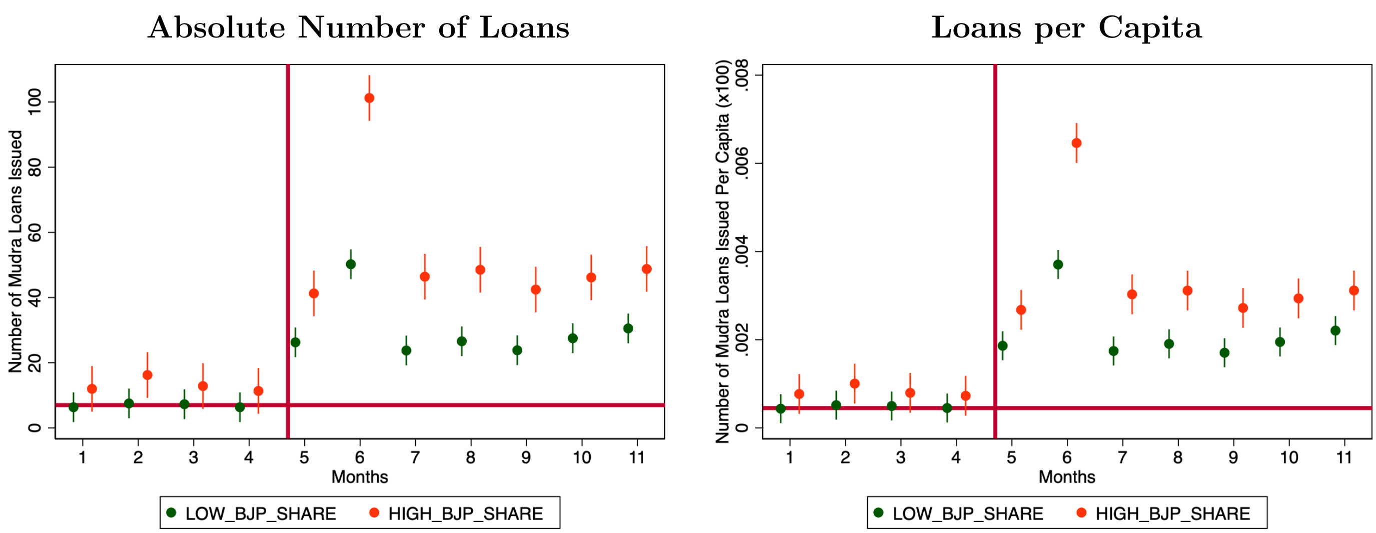


Figure 5. This figure plots the dynamics of Mudra Loans issuance across political constituencies above and below the median by BJP support. In Panel A, we first compute the total number of loans issued each month in each electoral district. We then compute the average number of loans issued across political constituencies with low and high BJP support, where the two categories are constructed by dividing the political constituencies into two groups of equal size based on the support for BJP in the 2014 elections. For each month and each group of political constituencies, we report the average number of Mudra loans issued and the associated confidence interval. The vertical red line indicates the start date of the promotion campaign. The results in Panel B repeat the analysis but focus on the total number of loans per capita (multiplied by 100 to make the y-axis labels more legible).

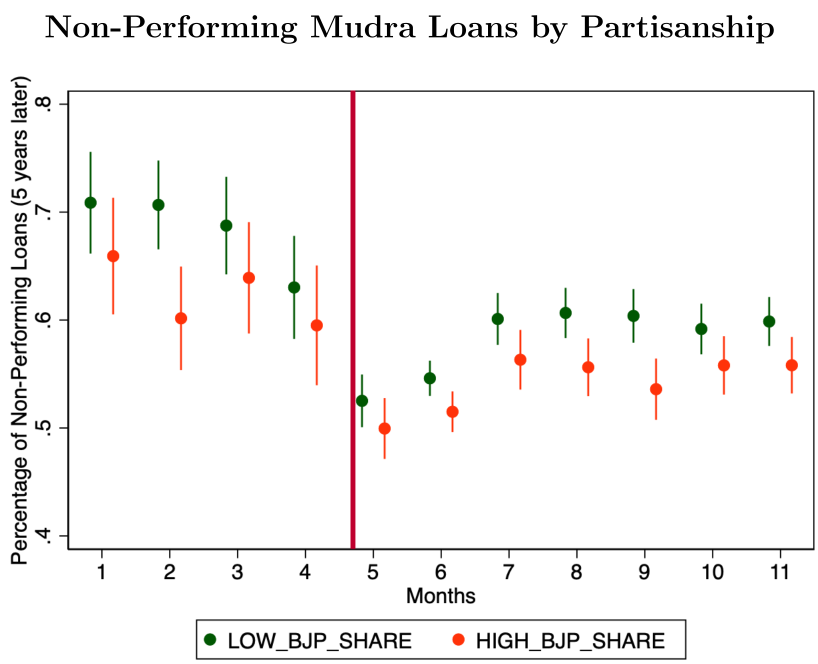


Figure 6. This figure plots the percentage of non-performing loans across electoral districts by BJP support before and after the promotion campaign. We first compute the percentage of loans categorized as non-performing, whether closed or not, as of October 2020. We then compute the value-weighted average across districts with low and high BJP support, where the two categories are constructed by dividing the political constituencies into two groups of equal size based on the support for BJP in the 2014 general elections. For each month and each group of districts, we report the value-weighted average of the percentage of non-performing loans and the associated confidence interval. The vertical red line indicates the date of the start of the Mudra loan promotion campaign.

Non-Mudra Loans Origination (Demand for Credit) by Partisanship

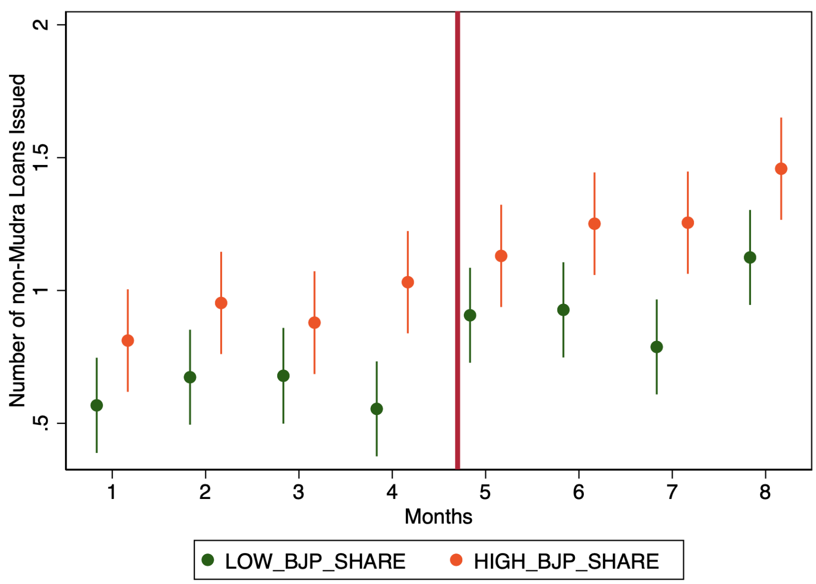
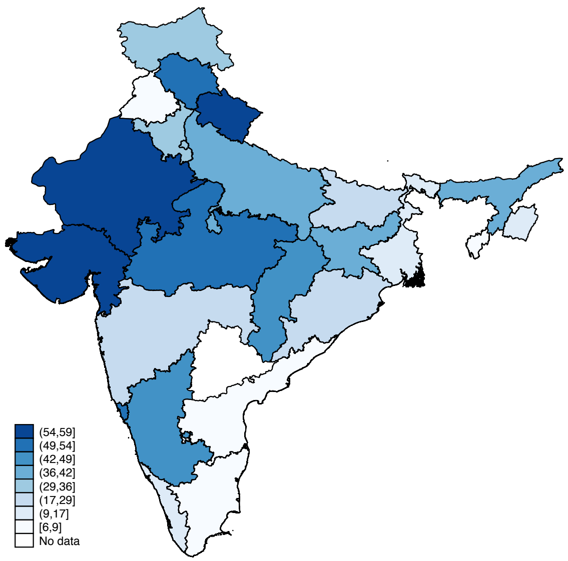


Figure 7. This figure plots the dynamics of non-Mudra loan issuance across electoral districts with low and high BJP support. We first compute the total number of non-Mudra loans issued each month in each district. We then compute the average number of loans issued across districts with low and high BJP support, where the two categories are constructed by dividing districts into two groups of equal size based on the support for BJP in the 2014 elections. For each month and each group of districts, we report the average number of non-Mudra loans issued and the associated confidence interval. The vertical red line indicates the date of the start of the Mudra loan promotion campaign.

Awareness: Partisanship and Search for Mudra Program During Promotion Campaign

Support for BJP (2014 elections)



Google Search Activity (Campaign)

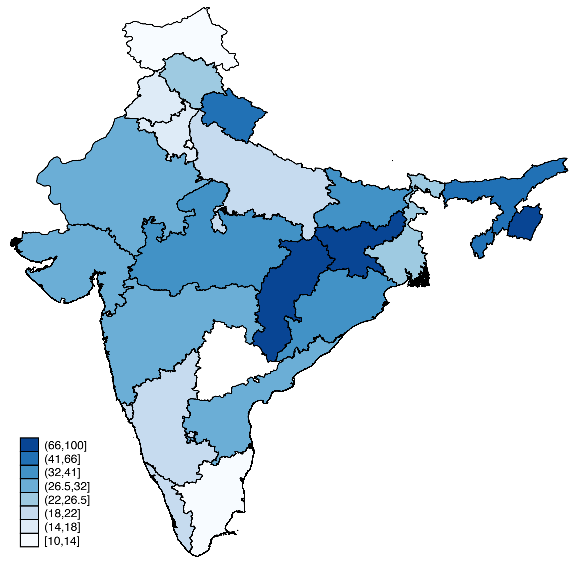


Figure 8. This figure plots on the left the choropleth map of BJP support by state in 2014. On the right, we plot the relative search activity on Google for the term “Mudra” around the promotion campaign period, from September 25th to October 15th, 2015.

Mudra Loans Origination in Partisan Contested vs. Not Contested Electoral Districts

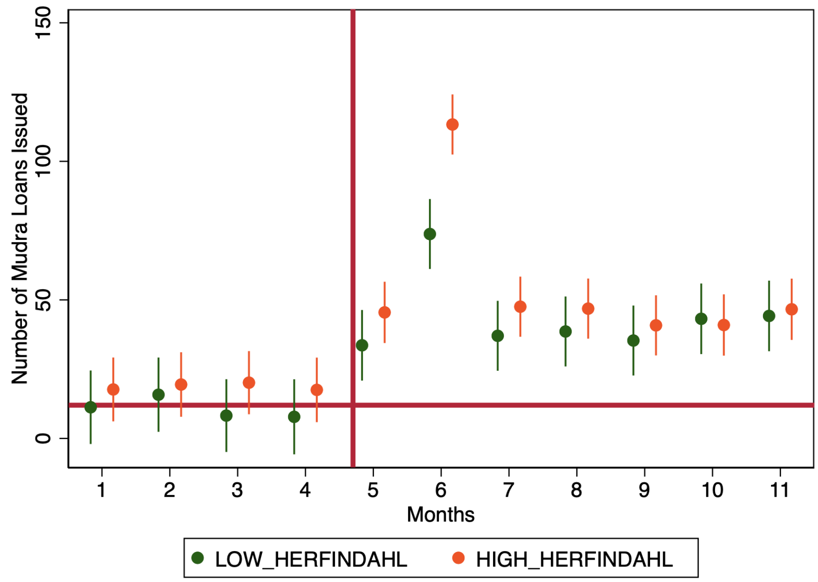


Figure 9. This figure plots the dynamics of Mudra Loans issuance across contested and not contested electoral districts. We first keep only the districts with BJP support between 45% and 55%. We then compute the adjusted Herfindahl index of vote shares across parties for the 2014 general elections in each electoral district as described in Section *2.1.*. Finally, we divide districts into two groups, low- and high-Herfindahl districts. For each month and each group of districts, we report the average number of Mudra loans issued and the associated confidence interval. The vertical red line indicates the date of the start of the Mudra loan promotion campaign.

Heterogeneous Effects in Partisan Districts by Borrower Types

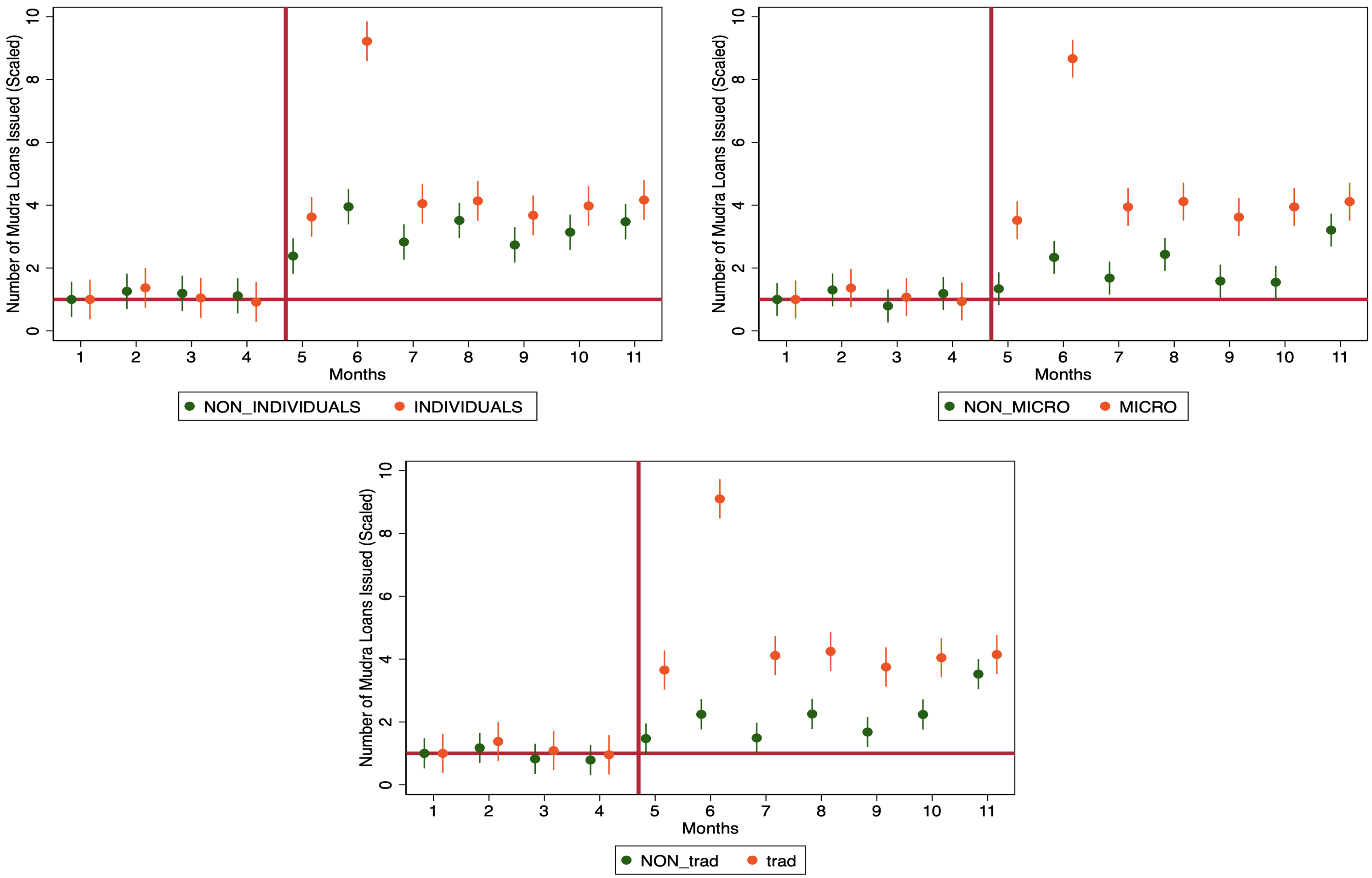


Figure 10. This figure plots the dynamics of Mudra loan issuance for different types of borrowers. In all Panels, we focus on electoral districts with high-BJP support, which are the ones that drive our main results. In the top left panel, we split the sample into individual and corporate (non-individual) borrowers. In order to make the results comparable across groups, we standardize the borrowing in April 2015 to be equal to 1. We then compute the average number of loans issued to individual and corporate borrowers. For each month and each type of borrower, we report the average number of Mudra loans issued and the associated confidence interval. The vertical red line indicates the date of the start of the Mudra loan promotion campaign. The top right panel repeats the exercise across micro and non-micro firms. The bottom panel repeats the exercise across trade & services firms and manufacturing firms.

Table 1. Summary Statistics

	N	mean	sd	p25	p50	p75
			Panel A. Loan Characteristics			
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 Issuance Timing			
	N	mean	sd	p25	p50	p75
Pre-Promotion Period	165,734	0.23	0.42	0.00	0.00	0.00
Promotion Period	165,734	0.33	0.47	0.00	0.00	1.00
Post-Promotion Period	165,734	0.44	0.50	0.00	0.00	1.00
			Panel C. Voting Data			
	N	mean	sd	p25	p50	p75
Vote share BJP	127,301	45.04	16.12	37.64	49.83	55.94
Vote share INC	150,924	26.73	14.58	15.63	30.37	38.11
Adjusted Herfindahl Index	165,734	0.34	0.08	0.28	0.35	0.41
			Panel D. 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

This table reports the summary statistics for the Mudra loans that are part of our loan-level sample. For each variable, we report in the first column the number of observations. In the remaining columns, we report the mean, standard deviation, 5th, 25th, 50th, 75th, and 95th percentiles of the variable's distribution. Panel A focuses on loan characteristics and contains results for the loan amount, interest rate, loan performance, and the gender of the borrower. Panel B focuses on the timing of the loans across three sub-periods. The first spans five months (May 2015-September 2015), the second the two months around the promotion (October 2015-November 2015), and the third the four months post promotion (December 2015-March 2015). Panel C presents summary statistics for voting characteristics of the political constituencies Mudra loans are issued in. We report the voting share of the Bharatiya Janata Party (BJP), the voting share of the Indian National Congress (INC) party, and the Adjusted Herfindahl index of the voting share across all parties running for elections in each electoral district. The adjusted Herfindahl index is computed in two steps. In the first step, we compute, in each electoral district, $H_c^* = \sum_{i=1}^{N} v_{i,c}^2$, where $v_{i,c}$ is the vote share of the party in electoral district c. In the second step, we compute $H_c = \frac{(H_c^* - 1/N)}{1-1/N}$ for $N > 1$ and $H_c = 1$ for $N = 1$. The measure ranges from 0 to 1, going from least to most concentrated. Panel D reports categorizations of the Mudra loans. The first variable is the percentage of micro loans, also known as *Shishu* loans. The second group are loans to individuals as opposed to corporations. Finally, the loans are classified in terms of their purpose: either trade & service or manufacturing.

Table 2. Partisanship and Mudra Loan Issuance—Electoral District Level

	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	— —	— —	— —	— —
Avg Interest Rate × During Campaign		-1.15 (-0.83)		-0.29 (-1.46)
Avg Interest Rate × After Campaign		-2.25* (-1.92)		-0.47** (-2.35)
Avg Female Share × During Campaign		-8.55 (-0.90)		-1.00 (-1.21)
Avg Female Share × After Campaign		-1.27 (-0.62)		0.12 (0.50)
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

This table reports the results of the following baseline panel regression at the district level:

$$\begin{aligned} Number/Value\ Loans_{j,t} = & \quad \alpha_j + \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ + & \quad \beta_2 \times BJP\ Share_j \times After\ Campaign_t \\ + & \quad \gamma_1 \times During\ Campaign_t + \gamma_2 \times After\ Campaign_t \\ + & \quad \delta \times BJP\ Share_j + X'_{j,t}\zeta + \epsilon_{j,t}, \end{aligned}$$

where $Number/Value\ Loans_{j,t}$ is the number of loans issued (columns (1)-(2)) or the aggregate value of Mudra lending (in millions of rupees, columns (3)-(4)) in district j and month t; α_j is a full set of district-level fixed effects; $BJP\ Share_j$ is the voting share for the BJP party in electoral district j in the 2014 general elections; $During\ Campaign_t$ is equal to 1 for the months October and November 2015 and 0 otherwise, and $After\ Campaign_t$ is equal to 1 for after November 2015 and equal to zero before November 2015. We standardize the variable $BJP\ Share_j$ so that it has a unit standard deviation. Standard errors are double clustered at the electoral district and monthly date levels. The second column adds two sets of interactions with the campaign and post-campaign periods. The first set of interactions is with the average interest rates of the Mudra loans approved in each month. The second is the average share of female borrowers in each month and district.

Table 3. Partisanship and Mudra Loan Issuance—Loan Level

	(1)	(2)	(3)	(4)
BJP Vote Share×	0.01**	0.01**	0.01***	0.01***
During Campaign	(3.04)	(3.05)	(3.22)	(3.25)
BJP Vote Share×	-0.00	-0.00	-0.00	-0.00
After Campaign	(-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

This table reports results on the timing of Mudra Loans issuance at the individual loan level as a function of the political support for the BJP party. We first construct a panel for each loan spanning April 2015-March 2016. The dependent variable is equal to zero for all months except for the month when the loan was issued. We then estimate the following specification:

$$\begin{aligned} Loan\ Issued_{i,j,t} &= \alpha + \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ &+ \beta_2 \times BJP\ Share_j \times After\ Campaign_t + \gamma_1 \times During\ Campaign_t \\ &+ \gamma_2 \times After\ Campaign_t + \delta \times BJP\ Share_j + \epsilon_{i,j,t}, \end{aligned}$$

where $Loan\ Issued_{i,j,t}$ is an indicator variable equal to 1 if loan i in electoral district j was issued on month t and 0 otherwise; $BJP\ Share_j$ is the voting share for the BJP party in electoral district j in the 2014 general elections; $During\ Campaign_t$ is equal to 1 for the months October and November 2015 and 0 otherwise, and $After\ Campaign_t$ is equal to 1 after November 2015 and equal to zero before November 2015. We standardize the variable $BJP\ Share_j$ to have a unit standard deviation. Standard errors are double clustered at the electoral district and monthly date levels. The second column adds loan-specific characteristics, such as interest rates and loan amounts, as additional covariates. It also absorbs the categories of the bank's assessment of borrowers' quality (IRAC) and the size group of the company (MSME). The third column adds the two borrower-specific characteristics we observe: gender and the type of organization based on the bank's 32 categories. The fourth column adds electoral district fixed effects.

Table 4. Partisanship and Mudra Loan Issuance:
Gender and Urban-Rural Divide

	(1)	(2)	(3)	(4)	(5)	(6)
Female Dummy× During Campaign	-0.03*** (-8.31)	-0.03*** (-8.27)	-0.02*** (-6.85)			
Female Dummy× After Campaign	-0.02*** (-5.67)	-0.02*** (-5.63)	-0.02*** (-5.64)			
Female Dummy	0.01*** (5.41)	0.01*** (5.42)	0.01*** (5.28)			
Rural Dummy× During Campaign				0.02 (1.61)	0.01 (1.08)	-0.00 (-0.43)
Rural Dummy× After Campaign				-0.01 (-1.25)	-0.00 (-0.70)	0.00 (0.61)
Rural Dummy				-0.00 (-0.26)	-0.00 (-0.22)	-0.00 (-0.22)
BJP Vote Share× During Campaign		0.01*** (3.21)	— —		0.02** (3.10)	— —
BJP Vote Share× After Campaign		-0.00 (-0.63)	— —		-0.01 (-1.43)	— —
During Campaign	0.15** (2.52)	0.15** (2.53)	— —	0.12** (2.54)	0.13** (2.63)	— —
After Campaign	0.07*** (4.38)	0.07*** (4.42)	— —	0.07*** (4.30)	0.06*** (4.65)	— —
BJP Vote Share	— —	— —	— —	— —	— —	— —
Constant	0.04* (1.90)	0.04* (1.91)	0.09*** (10.99)	0.05* (2.20)	0.04** (2.30)	0.09*** (11.84)
R-Square	0.03	0.03	0.09	0.03	0.03	0.09
Loan Characteristics	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Electoral District FE	✓	✓		✓	✓	
Electoral District×Month FE			✓			✓
Obs	1,033,054	1,033,054	1,033,054	544,797	544,797	544,753

This table reports results on the timing of Mudra Loans issuance at the individual loan level as a function of the political support for the BJP party. We first construct a panel for each loan spanning April 2015-March 2016. The dependent variable is equal to zero for all months except for the month when the loan was issued. We then estimate specifications equivalent to the one with Column (4) of Table 3, but we include in the first column only the interaction between the campaign dummies and the gender of the borrower. In the second column, we further add the double interactions between the electoral district vote for the BJP party interacted with the campaign dummies. In the third column, we include $Electoral\_District \times Month$ fixed effects. In columns (4) through (6), we repeat the exercise using a dummy variable indicating whether the borrower is in an urban or rural location. Standard errors are double clustered at the electoral district and monthly date levels.

Table 5. Supply-Side? Partisanship and Non-performing Mudra Loans

	(1)	(2)	(3)	(4)
BJP Vote Share× During Campaign	-0.01 (-1.61)	0.00 (0.29)	0.00 (0.27)	0.00 (0.63)
BJP Vote Share× After Campaign	-0.01** (-2.16)	0.00 (0.17)	0.00 (0.04)	0.00 (-0.10)
During Campaign	-0.05 (-1.13)	-0.03 (-0.71)	-0.04 (-0.81)	-0.01 (-0.71)
After Campaign	-0.02 (-0.49)	0.01 (0.20)	0.00 (0.02)	0.01 (0.39)
BJP Vote Share	0.01 (0.47)	-0.01 (-0.94)	-0.01 (-0.98)	— —
Interest Rate		-0.04*** (-13.40)	-0.04*** (-14.92)	-0.04*** (-16.13)
Loan Amount		-0.02*** (-2.94)	-0.02*** (-3.15)	-0.03*** (-6.14)
Female			-0.13*** (-6.09)	-0.13** (-5.80)
Constant	0.06*** (13.98)	1.12*** (11.05)	1.22*** (10.21)	1.24*** (18.15)
R-Square	0.00	0.09	0.10	0.19
Loan Characteristics		✓	✓	✓
Demographic Controls			✓	✓
Electoral District FE				✓
Obs	129,828	127,160	127,153	127,153

This table reports results on the non-performance of Mudra Loans at the individual loan level as a function of BJP support. We estimate the following baseline regression specification:

$$\begin{aligned} Non-Perform\ Ind_{i,j,t} = {} & \alpha + \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ & + \beta_2 \times BJP\ Share_j \times After\ Campaign_t + \gamma_1 \times During\ Campaign_t \\ & + \gamma_2 \times After\ Campaign_t + \delta \times BJP\ Share_j + \epsilon_{i,j,t}, \end{aligned}$$

where $Non-Perform\ Ind_{i,j,t}$ is an indicator variable equal to 1 if the loan i in electoral district j issued on month t has been recorded as nonperforming as of October 2020, and 0 otherwise; $BJP\ Share_j$ is the BJP vote share in electoral district j; $During\ Campaign_t$ is equal to 1 for the months of October and November 2015, and 0 otherwise; and $After\ Campaign_t$ is equal to 1 for after November 2015 and equal to zero before November 2015. We standardize the variable $BJP\ Share_j$ to have a unit standard deviation. Standard errors are double clustered at the electoral district and monthly date levels. The second column adds loan-specific characteristics, such as interest rates and loan amounts, as additional covariates. It also absorbs the bank's assessment of the quality of the borrower (IRAC) and the size group of the company (MSME). The third column adds the two borrower-specific characteristics we observe: gender and the type of organization based on the bank's 32 categories. The fourth column adds electoral district fixed effects.

Table 6. Effects for States Ruled by BJP and non-BJP Parties

	(1)	(2)	(3)	(4)
	BJP ruled	**Non-BJP ruled**	**BJP ruled**	**Non-BJP ruled**
BJP Vote Share×	0.02*	0.02**	0.02**	0.02**
During Campaign	(1.95)	(2.66)	(2.49)	(2.99)
BJP Vote Share×	-0.01	-0.01**	-0.01	-0.01*
After Campaign	(-0.85)	(-2.75)	(-0.91)	(-1.97)
During Campaign	0.11**	0.14**	0.13**	0.16**
	(2.64)	(2.51)	(2.44)	(2.41)
After Campaign	0.08***	0.05***	0.07***	0.05***
	(6.01)	(3.48)	(5.50)	(3.25)
BJP Vote Share	-0.00	0.00	—	—
	(-0.38)	(0.47)	—	—
Constant	0.04***	0.05***	0.04**	0.04*
	(3.66)	(3.53)	(2.31)	(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

This table reports results on the timing of Mudra Loans issuance at the individual loan level as a function of BJP support, estimating the relation separately for states that are ruled by BJP-affiliated parties and states that are not. We first construct a panel for each loan spanning April 2015-March 2016. The dependent variable is equal to zero for all months except for the month when the loan was issued. We then estimate the following baseline regression specification:

$$\begin{aligned} Loan\ Issued_{i,j,t} = \alpha &+ \beta_1 \times BJP\ Share_j \times During\ Campaign_t \\ &+ \beta_2 \times BJP\ Share_j \times After\ Campaign_t + \gamma_1 \times During\ Campaign_t \\ &+ \gamma_2 \times After\ Campaign_t + \delta \times BJP\ Share_j + \epsilon_{i,j,t}, \end{aligned}$$

where $Loan\ Issued_{i,j,t}$ is an indicator variable equal to 1 if the loan i in electoral district j was issued on month t and 0 otherwise; $BJP\ Share_j$ is the voting share for the BJP party in electoral district j; $During\ Campaign_t$ is equal to 1 for the months October and November 2015 and 0 otherwise, and $After\ Campaign_t$ is equal to 1 for after November 2015 and equal to zero before November 2015. We standardize the variable $BJP\ Share_j$ to have a unit standard deviation. Standard errors are double clustered at the electoral district and monthly date levels. The first column focuses on states that are ruled by BJP-affiliated parties, and the second column on states that are not. The remaining two columns repeat the analysis, including loan characteristics, demographic controls, and electoral district fixed effects.

Table 7. Partisanship and Mudra Loan Issuance
Contested vs. Non-contested Districts

	(1)	(2)	(3)	(4)
BJP Vote Share×Polarization×	0.12**	0.13**	0.13**	0.17***
During Campaign	(2.63)	(2.90)	(2.91)	(3.20)
BJP Vote Share×Polarization×	-0.01	-0.01	-0.01	0.03
After Campaign	(-0.18)	(-0.19)	(-0.18)	(0.86)
BJP Vote Share×	0.08**	0.08**	0.08**	0.08***
During Campaign	(2.95)	(3.05)	(3.05)	(3.27)
BJP Vote Share×	0.06**	0.06**	0.06**	0.06**
After Campaign	(2.73)	(2.71)	(2.71)	(2.47)
Polarization×	-0.07**	-0.07**	-0.07**	-0.08**
During Campaign	(-2.68)	(-2.87)	(-2.87)	(-2.85)
Polarization×	-0.02*	-0.02	-0.02	-0.03**
After Campaign	(-1.85)	(-1.65)	(-1.63)	(-2.42)
During Campaign	0.10*	0.10*	0.10*	0.10*
	(2.18)	(2.17)	(2.17)	(2.17)
After Campaign	0.04***	0.04***	0.04***	0.04***
	(3.89)	(3.94)	(3.94)	(3.88)
BJP Vote Share	-0.03**	-0.03**	-0.03**	—
	(-2.54)	(-2.87)	(-2.88)	—
Polarization	0.01**	0.01**	0.01**	—
	(2.42)	(2.76)	(2.78)	—
Interest Rate		-0.00	-0.00	-0.00
		(-0.01)	(-0.01)	(-0.01)
Loan Amount		0.00	0.00	0.00
		(0.04)	(0.05)	(0.04)
Female			0.00	0.00
			(0.01)	(-0.01)
Constant	0.05***	0.05***	0.05***	0.04**
	(5.79)	(3.49)	(3.42)	(2.90)
R-Square	0.03	0.03	0.03	0.03
Loan Characteristics		✓	✓	✓
Demographic Controls			✓	✓
Electoral District FE				✓
Obs	504,948	497,436	497,436	497,436

This table reports results on the timing of Mudra Loans issuance at the individual loan level as a function of political polarization within a given electoral district, which we use as a proxy for the extent to which the electoral district is contested. We estimate the regression:

$$\begin{aligned} Loan\ Issued_{i,j,t} = \alpha &+ \beta_1 \times BJP\ Share_j \times Polarization_j \times During\ Campaign_t \\ &+ \beta_2 \times BJP\ Share_j \times Polarization_j \times After\ Campaign_t \\ &+ \gamma_1 \times BJP\ Share_j \times During\ Campaign_t + \gamma_2 \times BJP\ Share_j \times After\ Campaign_t \\ &+ \delta_1 \times Polarization_j \times During\ Campaign_t + \delta_2 \times Polarization_j \times After\ Campaign_t \\ &+ \theta_1 \times During\ Campaign_t + \theta_2 \times After\ Campaign_t \\ &+ \zeta \times BJP\ Share_j + \xi \times Polarization_j + \epsilon_{i,j,t}, \end{aligned}$$

where all quantities and specifications are defined as in the caption to Table 3, except for $Polarization_j$ that denotes the normalized Herfindahl Index of each party's vote share in the 2014 general elections at the district level—see Section *2.1.* for details about its construction. To be consistent with Figure 9, we estimate these regressions using only electoral districts in which BJP support is between 45% and 55%, and hence for which the level of BJP support is similar and close to the absolute majority.

Online Appendix:
Political Partisanship and the Transmission of Fiscal Policy

Francesco D'Acunto, Pulak Ghosh, Alberto G. Rossi

Not for Publication

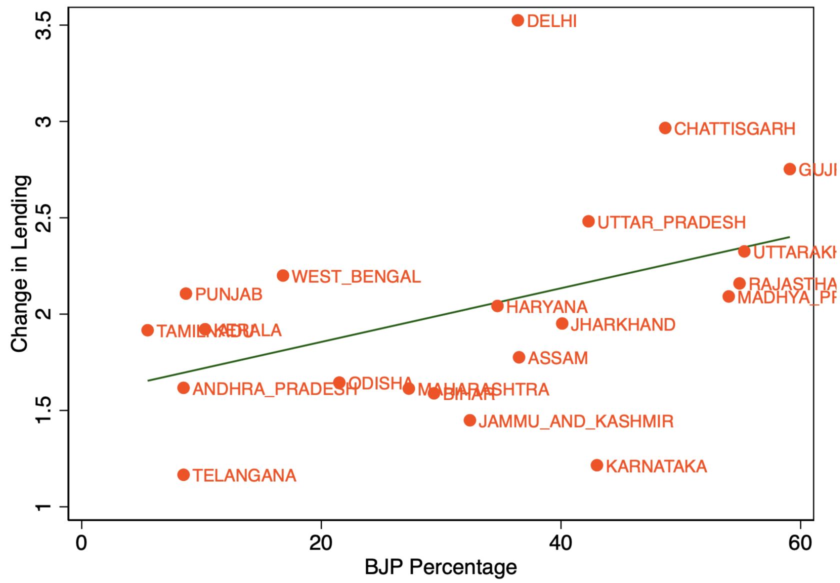
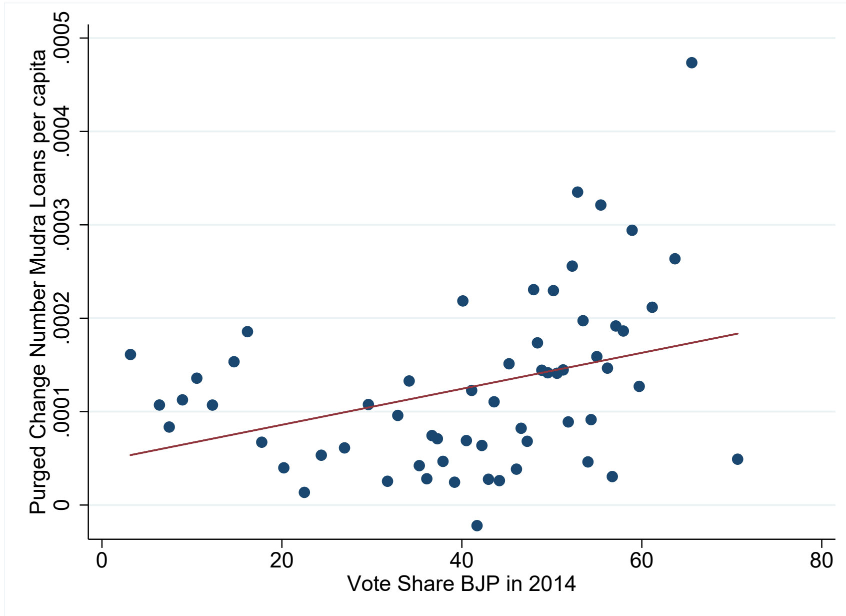


Figure A.1 This figure reports results relating the take-up of Mudra loans to the support for the BJP party across states. We first compute, at the state level, the support for the BJP party as well as the total number of Mudra loans issued each month. We then compute the growth in loans issued in each state over the period October-December 2015, after the Mudra Loan promotion program started, compared to the period June-August 2015, and report the results in the figure. The x-axis reports the average support for the BJP, while the y-axis reports the differential growth in Mudra loans post promotion, compared to before.


Purged Change Number Mudra Loans per capita
0
.0001
.0002
.0003
.0004
.0005
0
20
40
60
80
Vote Share BJP in 2014

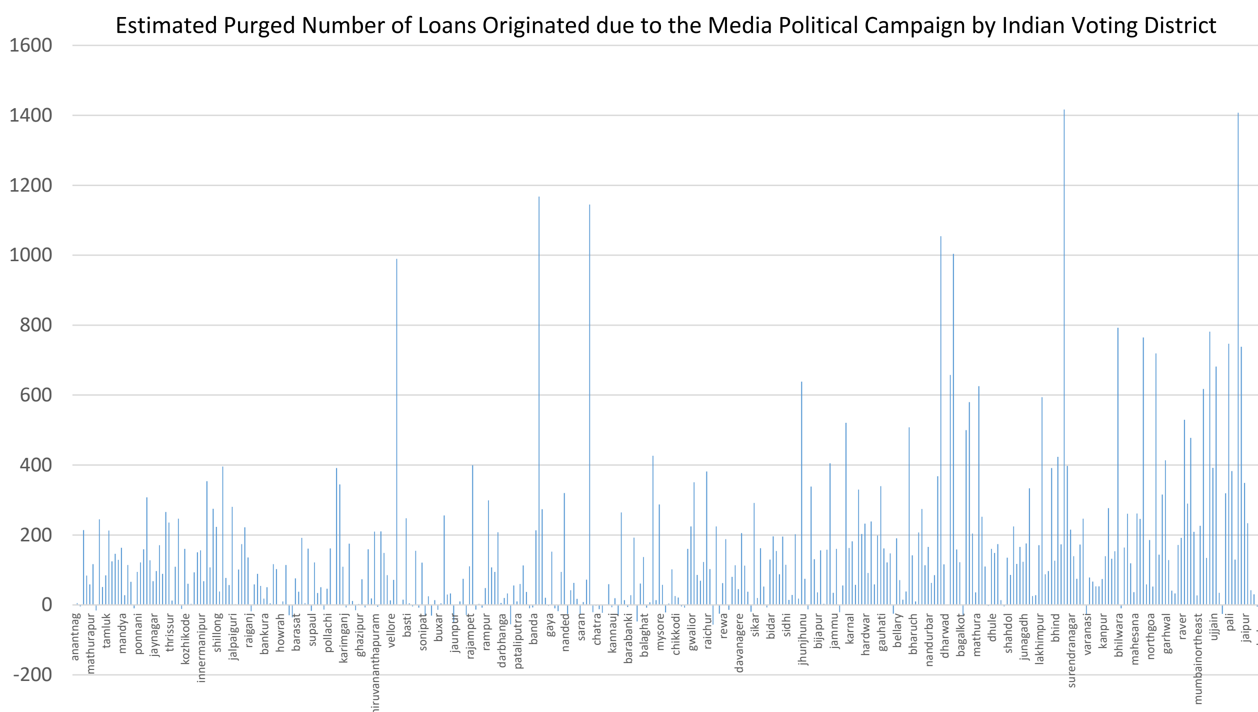

Estimated Purged Number of Loans Originated due to the Media Political Campaign by Indian Voting District
1600
1400
1200
1000
800
600
400
200
0
-200
anantnag
mathurapur
tamluk
mandya
ponnani
jaynagar
thrissur
kozhikode
innermanipur
shillong
jalpaiguri
raiganj
bankura
howrah
barasat
supaul
pollachi
karimganj
ghazipur
thiruvananthapuram
vellore
basti
sonipat
buxar
jaunpur
rajampet
rampur
darbhanga
pataliputra
banda
gaya
nanded
saran
chatra
kannauj
barabanki
balaghat
mysore
chikkodi
gwalior
raichur
rewa
davanagere
sikar
bidar
sidhi
jhunjhunu
bijapur
jammu
karnal
hardwar
gauhati
bellary
bharuch
nandurbar
dharwad
bagalkot
mathura
dhule
shahdol
junagadh
lakhimpur
bhind
surendranagar
varanasi
kanpur
bhilwara
mahesana
northgoa
garhwal
raver
mumbainortheast
ujjain
pali
jaipur
vadodara

Figure A.2

Table A.1. Partisanship, Information Acquisition, and Mudra Loans Issuance

	(1)	(2)	(3)	(4)	(5)
BJP Vote Share×	0.01**	0.01**	0.01**	0.01**	0.01**
During Campaign	(2.76)	(2.78)	(2.77)	(2.86)	(2.82)
BJP Vote Share×	-0.00	-0.00	-0.00	-0.00	-0.00
After Campaign	(-0.61)	(-0.60)	(-0.60)	(-0.61)	(-0.62)
Mudra Search×	0.01**	0.01**	0.01**	0.01**	0.01*
During Campaign	(2.35)	(2.37)	(2.37)	(2.39)	(2.08)
Mudra Search×	0.00	0.00	0.00	0.00	0.00
After Campaign	(1.05)	(1.01)	(1.02)	(1.01)	(0.77)
During Campaign	0.12**	0.12**	0.12**	0.12**	0.12**
	(2.57)	(2.56)	(2.56)	(2.56)	(2.59)
After Campaign	0.07***	0.07***	0.07***	0.07***	0.07***
	(4.70)	(4.70)	(4.70)	(4.70)	(4.82)
BJP Vote Share	-0.00	-0.00	-0.00	—	—
	(-0.40)	(-0.29)	(-0.29)	—	—
Mudra Search	-0.00	-0.00	-0.00	—	—
	(-1.66)	(-0.79)	(-0.79)	—	—
BJP Vote Share× Mudra Search×					0.01
During Campaign					(1.20)
BJP Vote Share× Mudra Search×					-0.00
After Campaign					(-0.91)
Constant	0.05***	0.04**	0.04**	0.04**	0.04**
	(3.36)	(2.39)	(2.38)	(2.57)	(2.57)
R-Square	0.03	0.03	0.03	0.03	0.03
Loan Characteristics		✓	✓	✓	✓
Demographic Controls			✓	✓	✓
Electoral District FE				✓	✓
Obs	1,376,551	1,357,411	1,357,356	1,357,356	1,357,356

This table reports results on the timing of Mudra Loans issuance at the individual loan level as a function of the political support for the BJP party. We first construct a panel for each loan spanning April 2015-March 2016. The dependent variable is equal to zero for all months except for the month when the loan was issued. We then estimate a variation of Equation (2) to which we add as regressors the standardized state-level Google Search activity for the term "Mudra" over the period September 20-October 24, 2015, which we also interact with the period of the campaign as well as the period after the campaign ended. Standard errors are double clustered at the electoral district and monthly date levels. The second column adds loan-specific characteristics, such as interest rates and loan amounts, as additional covariates. It also absorbs other loan characteristics, such as the bank's assessment of the quality of the borrower (IRAC) and the size of the company (MSME). The third column adds the two borrower-specific characteristics we observe: gender and the type of organization based on the bank's 32 categories. The fourth column adds electoral district fixed effects, effectively controlling for all static characteristics across different political constituencies. Finally, in the fifth column, we compute the triple interactions between the campaign and the post-campaign period, the Google Search activity for the "Mudra" term, and BJP support.