Politics and Real Firm Activity: Evidence from Distortions in Bank Lending in India

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Abstract

This paper provides novel evidence on a particular real cost of political interference on banks—preferential lending to politically important sectors crowds out lending to other sectors in the economy. Analyzing staggered state elections in India, I show that politicians influence banks to increase lending to farmers before elections, which crowds out lending to manufacturing firms. These lending distortions are larger in locations where farmers have more political weight. Comparing firms in states that have an election in a given year against comparable firms in states that do not, I find that the reduced availability of bank credit forces firms to use up their cash reserves, reduce production, lay off workers, and operate at lower utilization rates. Overall, my results suggest that interference from the political environment can lead to costly crowding-out of real firm activity.

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1. Introduction

Around the world, government ownership of banks is large and pervasive (La Porta et al. (2002)). As a result, banks could be subject to political capture. In particular, politicians can distort credit allocation in the economy for personal or electoral gains. A growing literature examines how political favors arise through the banking sector in the form of cheap and preferential lending to particular groups of borrowers (Sapienza (2004), Khwaja and Mian (2005)). However, very little is known about the real cost of such distortions. One obvious cost is on the banks that are forced to make these preferential lending. But other agents in the economy could also bear the direct cost of these distortions. For example, such distortions could crowd out lending to other sectors of the economy. In this paper, I provide evidence of this crowding-out and argue that the cost is non-trivial.

Using a unique setting in India and confidential loan-level data from one of the largest banks in India, I show that politicians influence the bank to increase lending to farmers before elections—a finding documented in Cole (2009)—at the cost of lending to manufacturing firms. Consistent with political interference, I find the increase in agricultural lending and the decrease in lending to the manufacturing sector are more pronounced for bank-branches in locations where farmers have more political weight. The crowding-out in lending to the manufacturing sector is greater for branches located far away from their respective regional head-offices—suggesting efficient information flow between branch and head-office alleviates constraints that lead to crowding-out. This political interference has real effects on manufacturing firms. Using detailed plant-level data for manufacturing firms in India, my analysis shows that lack of bank funding forces firms to use up their cash reserves, reduce production, cut investments and lay off workers. This interference appears costly: reduced production during elections lowers plant utilization rates and renders productive resources idle.

Identifying the effects of political interference in the economy is a difficult task. The primary challenge is to overcome the problem of omitted variables—the same underlying economic variables might drive both sluggish firm activity and government's decision to intervene. For example, the economy might genuinely need government intervention to correct a market failure when economic conditions are deteriorating, and one could erroneously interpret this involvement as political interference that directly harms economic activity.

Studying political interference during pre-scheduled elections alleviates this identification problem. If the election schedule is pre-determined and fixed, then by construction omitted variables do not drive the election cycle.[1] At the same time, incumbent politicians have an incentive to interfere in the economy before elections to enhance their chances of being re-elected to power (Nordhaus (1975), Lindbeck (1976), Rogoff

[1] Although this ensures that the election cycle is exogenous, an election itself could drive economic variables, which in turn could affect firms. I discuss this issue in detail later in this section.

(1990)). The cycle thus provides natural variation in the intensity of political interference that is not driven by the omitted economic variables that could directly affect firm activity.

In this paper, I study staggered state elections. Studying state elections instead of national elections provides additional advantages. Since each of the 30 states in India follows its own five-year election cycle, I can perform a simple difference-in-difference analysis and compare lending and firm activity in a state with an upcoming election against those in states with no upcoming elections in a given year. Hence, I can control for macro-economic changes that directly affect all firms (time trends). For example, it helps me rule out changes in monetary policy or banking regulations as driving my results. Similarly, business cycles do not drive my results. To allay concerns that business cycle at a local level could drive my results, I further restrict the control group to nearby states that do not have an upcoming election. Another advantage of using state elections is that it allows me to work with a much larger sample of elections. During my sample period of 1999-2008, India held 60 state elections and only 2 federal elections.

Using lending data from one of the largest banks in India, which is majority-owned by the federal government, I show that the bank increases lending to agriculture during election years at the expense of lending to manufacturing firms. I find average agricultural sector lending during election years was 9.4% higher than during non-election years. This increased lending comes at the expense of the manufacturing sector. Lending to manufacturing firms during the same period was 2.7% lower compared to non-election years. Furthermore, I find that these effects—an increase in agricultural lending and a decrease in manufacturing lending—are stronger in (i) election constituencies where elections are tightly contested, and (ii) at branches located in areas where a larger proportion of voters are employed in agriculture.[2] The strong relationship between the size of the credit cycle and the proportion of voters relying on agriculture lends credibility to the preferred explanation for observed behavior: politicians influence banks to lend more to farmers before elections in order to win their votes.

Why do politicians favor agriculture over manufacturing? As per the 2001 census, 57% of the total workforce in India was engaged in agriculture, whereas the manufacturing sector employed just 13% of the workforce. With the majority of the workforce engaged in agriculture, the sector has more political "weight" than the manufacturing sector. Furthermore, subsidized bank credit seems especially high on farmers' priority list. Karnik and Lalvani (1996) document that farmers in Indian states with stronger farm lobbies receive more subsidized bank credit than farmers elsewhere. Hence, wooing farmers with cheap loans during elections seems attractive.

To examine the effect of this credit squeeze on manufacturing firms, I use detailed plant-level data collected by the Annual Survey of Industries (ASI). One advantage of using this dataset covering all plants

[2] India has a parliamentary system where voters elect their local representative at the constituency level. Election competition can hence be defined at the constituency level, providing within-state variation in closeness of elections.

in India is to cross-check the results of the bank lending data, which comes from just one bank and might not be representative of the entire banking sector. Reassuringly, I find similar results when examining firm-level debt for all manufacturing firms in the country. Using a specification with region-year and industry-year fixed-effects, I find that firm leverage falls by 2% during elections. The fall in leverage is accompanied by a 2% fall in the cash holdings on the balance sheet of firms. The evidence on cash holdings is consistent with the precautionary savings role of cash: firms smooth the effect of a credit squeeze by drawing down their cash reserves.

This funding squeeze affects real decisions of firms. Firms cut investments by 3.6% and lay off 3.3% of their temporary employees. The reduction in availability of bank loans forces firms to reduce their scale of operations. Production during an election year is 2.8% below production two years prior to election. Because adjustment to capital stock is costly and slow, lower production adversely affects utilization of fixed assets. Capital utilization falls by 2.9% during an election year.

Politically motivated lending distortion is not the only mechanism through which elections can affect firm activity. For example, my results could be driven by local economic factors that covary with the election cycle. The paper provides direct evidence to rule out two alternative explanations—(i) fall in demand for manufacturing goods during elections, and (ii) political uncertainty. Additionally, the strong relationship between the size of the credit cycle and the proportion of voters relying on agriculture lends credibility to the political interference explanation. Furthermore, I show that publicly traded firms that do not rely on their local bank branches for financing are not affected during elections. Overall, the evidence provided in the paper is more consistent with a politically motivated bank lending channel. Any other explanation would have difficulty rationalizing all the findings.

My work is closely related to Cole (2009). Using aggregate bank lending data at the district level, Cole finds that government-owned banks increase agricultural lending in an election year. Targeting is tactical, with large increases in districts with a close election. Cole does not find any measurable increase in agricultural output or investment during election years, suggesting additional borrowing is not productive.

By contrast, my paper *directly* focuses on the real cost of this lending distortion. Using micro data at the bank branch level that allows me to exploit cross-sectional variation, I establish crowding-out in lending to manufacturing firms. Using plant-level data for firms in the manufacturing sector, I provide novel evidence that political favors in the banking sector has real and significant costs for firms. A fall in plant utilization rates during elections renders some productive capacity idle. I estimate that had firms maintained their utilization level during the election year and put all their productive resources to use, the sector would have added another 0.20% to India’s GDP.

My paper contributes to a growing literature on the political economy of firms. Previous work in this area has examined how political favors arise via the banking system. Carvalho (2014) shows that firms eligible for government bank lending expand employment in politically attractive regions near elections in Brazil. Khwaja and Mian (2005) provide evidence that politically connected firms borrow 45% more and have 50% higher default rates. Claessens et al. (2008) show that Brazilian firms that provide campaign contributions receive substantially higher bank financing. While all these papers focus on the quid-pro-quo relationship between the politicians and firms, my paper contributes by examining the cost of such relationships. I show that political favors can result in costly crowding-out of other productive agents in the economy.[3]

This paper also adds to the literature on the political business cycle. The theory on the political business cycle predicts that incumbents manipulate fiscal and monetary policies to induce greater economic activity before elections. Drazen (2000) provides an excellent review of this literature. The consensus view is that developing economies and recent democracies are more susceptible to such manipulations. Dinc (2005) shows that government-owned banks increase their lending in election years relative to private banks. My work establishes a clear cycle in bank lending, with some sections of the economy experiencing growth in credit at the expense of others.

Finally, my findings add to the literature on the real effects of credit constraints. Lemmon and Roberts (2010) find that firms that were cut from the below-investment-grade bond market due to an exogenous contraction in this market could not arrange for alternative sources of financing, leading to an almost one-for-one decline in net investment. Campello et el. (2010) find that financially constrained firms burned more cash and planned deeper cuts in tech spending, employment and investment during the financial crisis compared to their unconstrained counterparts. Butler and Cornaggia (2011) use an exogenous shift in product demand to show that higher access to finance improves productivity. I add to this literature by showing that even when a tightening in credit supply is anticipated, firms that predominantly rely on banks for their financing are unable to completely hedge against the adverse effects of credit squeeze. I also show that lower credit availability not only affects a firm's investment decision, but also its production and employment decisions and production efficiency.

2. Background on Banking and Elections in India

2.1. Banking

Government majority-owned (public sector) banks dominate the banking system in India. Public sector banks came into existence via several phases of nationalization, the last of which happened in 1980

[3] A related literature looks at the political economy of financial regulations. See, for example, Kroszner and Strahan (1999), Rajan and Zingales (2003), Benmelech and Moskowitz (2010), and Rajan and Ramcharan (2011).

when six private banks (with deposits over 2 billion Rupees) were nationalized, bringing the total number of public banks to 28. Public banks are majority owned by the federal government. Most of them are publicly listed in India.[4]

The Reserve Bank of India (RBI) regulates all banks in India, which are held to the same standards. Apart from the fact that the central government appoints senior management and the majority of the board members, the organizational structure of public and private banks is very similar. This is partly borne out of the fact that public banks were created by nationalizing healthy private banks. These banks continued to function as corporate entities and retained a majority of the workforce and organizational structure post-nationalization. Table 1 decomposes total bank lending into various sectors by bank groups. Clearly, the credit outlay by the two groups is very similar.

Banks in India are required to provide at least a specified fraction of their total credit outlay to agriculture and to micro and small enterprises (priority sector lending).[5] Additionally, in the past, they were required to open two branches in unbanked locations for every new branch opened in a banked location. These two policies had a tremendous impact on the extension of credit to underserved areas. Between 1972 and 1990, the total number of bank branches in India more than quadrupled, from 14,650 branches to over 60,000 branches.[6] Burgess and Pande (2005) argue this led to a substantial decline in poverty in rural areas. At the same time, penetration of banks into deep recesses of the country made them very attractive for political capture, especially because the sector was overwhelmingly under government control.

2.2. State Elections

India has a federal structure with elections held at both national and state levels. The constitution requires elections for state assembly to be held every five years. Elections are staggered, with each state following its own five-year cycle. The party or coalition with a simple majority is invited to form the state government. Elections can be called early if the assembly is dissolved (either because the ruling government loses the majority or wants an early election, or by directions from the federal government under special circumstances). As described later in the paper, I ensure that my results are not driven by early elections.

Table 2 tabulates state elections by year for our sample period. At least three state elections were held every year. Different states may hold elections in different months of the same year (unlike in the United States where general elections happen on the Tuesday after the first Monday in November). The Election Commission of India, an autonomous body, is responsible for administering the electoral process.

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[4] The private banking sector, consisting of both domestic and foreign players, contributed around 10% of total bank credit during the 1999-2008 period.

[5] Banks are required to direct at least 40% of their total credit outlay to priority sector. Other categories that come under priority lending are education, housing, export credit and some weaker sections of society.

[6] Source: Bank Statistics, Reserve Bank of India.

Voters cast their ballots to elect their local representative (called Member of Legislative Assembly (MLA)) at the assembly constituency level. On average, each state has 137 assembly constituencies. Election at the constituency level follows a first-past-the-post system, with the candidate with the maximum valid votes winning the election. Figure 1 illustrates the parliamentary form of state elections in India. The party or coalition with a simple majority of MLAs is invited to form the government at the state level. Therefore, voters do not directly choose the head of the state government, but rather their local representative. As a result, the competitiveness of an election is defined at the assembly constituency level.

2.3. Political Influence on Banks

The federal government owns a majority stake in each public sector bank in India. By virtue of its majority ownership, the federal government appoints senior management and the majority of board members of public sector banks. Although state governments and other locally elected representatives do not enjoy any control over these banks via ownership, regulatory provisions allow them to have a significant influence over banks' lending decisions at the local branch level.

The Lead Bank Scheme, instituted in 1969, designates a bank with a significant presence in a district to be its "Lead". Districts are local administrative units that form the tier immediately below the states. Per census data of 2001, India contained 593 districts, with an average of around 20 districts per state. The median district contains nine electoral constituencies. The Lead Bank Scheme aims to provide collective action by banks and other financial institutions in the implementation of banking schemes for improvement in the district economy. To help achieve this loosely defined goal, the RBI set up District Level Consultative Committees (DLCCs) with the Lead Bank as its convener and the District Collector as the chairman. The District Collector is the senior-most bureaucrat at the district. The state government controls the deputation and transfer of District Collectors. All commercial banks, financial institutions, and various state government departments are members of the committee. A major task of the committee is to expand the reach of banking facilities to unbanked areas and to ensure proper implementation of priority sector lending. In particular, the committee plays an active role in identifying areas within district where banking facilities in general and priority sector lending in particular (including agricultural and small-scale industries) need special attention.

To ensure proper co-ordination across districts for initiatives that crossed district boundaries, and to ensure periodic review of the Lead Bank Scheme at the state level, State Level Banker's Committees (SLBCs) were set up in 1976. The committee is chaired by a high-ranking state government official and its members include representatives from various state government departments. The scope of the SLBC includes resolving regional imbalances in the availability of banking facilities, resolving regional imbalances in deployment of credit, review of district credit plans, and review of credit flow to small borrowers in the priority sectors.

Through these schemes, the state government and elected representatives from the state wield substantial influence over a bank's lending decisions. State politicians have no qualms about using this influence to garner popular votes during elections. For example, Cole (2009) quotes the following from *Financial Express*:

"Two main contenders in the Rajasthan assembly elections...are talking about economic well-being in order to muster votes. No wonder then that easier bank loans for farmers, remunerative earnings from agriculture on a bumper crop as well as uninterrupted power supply appear foremost in the manifestoes of both the parties"[7]

More recently, *FirstPost* reports the following regarding farm loans during two state elections in 2014:

"Indian state-run banks are set to bear the burden of yet another politically sponsored loan waiver program. The newborn twin states ... are set to implement the poll bonanza promised by their political heads to their voters during recent elections. While Andhra Pradesh cabinet had officially approved the Rs 43,000 crore loan waiver, Telangana is busy cutting out the final structure of the waiver that could run into several thousand crores"[8][9]

Why is agricultural credit particularly attractive to politicians? Per the 2001 census, 57% of the total workforce in India was engaged in agriculture, although its share in GDP stood at just 19.43%. Although the share of total bank lending to agriculture was just 11% (amount of loans), it constituted 38% of all bank loans (number of loans).[10] With the majority of voters dependent on agriculture, wooing farmers with cheap loans seems attractive. As noted earlier, subsidized bank credit remains high on farmers' priority list. Karnik and Lalvani (1996) document that farmers in Indian states with stronger farm lobbies receive more subsidized bank credit than farmers elsewhere. Hence, criticizing such government initiatives is especially difficult for opposition politicians.

Furthermore, farm lobbies are among the most influential interest groups in India. An extensive literature documents the influence of farm lobbies on government policies (Bardhan (1984), Haque and Verma (1988)). For example, agricultural income is tax-exempt in India. Federal and state governments provide large scale input subsidies to the sector (Pursell and Gulati (1993)). Starting with Becker (1983), the literature on political interest groups argues such groups play a role in formulating government policies. Bardhan and Mookherjee (2000) provide a model where special interest groups receive targeted benefits in

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[7] Financial Express, November 30, 2003
[8] FirstPost, July 29, 2014
[9] 1 crore = 10 million
[10] Manufacturing sector employed 13% of the country's workforce while availing 43% of the bank credit.

exchange for campaign support to mobilize the majority of votes needed for re-election. The evidence provided in this paper is consistent with such arguments.

3. Data Description

3.1. Bank Data

Information on bank loans comes from the loan books of one of India's largest bank. The database contains information about each loan outstanding at the end of the fiscal year (March 31) at each branch of this government majority-owned bank. All banks are mandated to provide this information to the RBI in a specified format. I obtain disaggregated loan-level data for the bank directly from the RBI. In addition to the amount outstanding, the data set has information on the interest rate, type of loan, the borrower's industry, and loan performance, among other things. The data is available for the period 1999-2007. The dataset contains 1,365,425 loan observations from 2,800 branches of the bank.

Table 3 Panel A shows summary statistics on bank data. The unit of observation for lending data is branch-year. There are a total of 23,252 branch-year observations from 2,800 branches over the 10-year period. Not all bank branches lend to both agricultural and manufacturing sectors.

3.2. Firm Data

Firm-level panel data comes from the Annual Survey of Industries (ASI), conducted by the Ministry of Statistics and Program Implementation (MoSPI) in India. The ASI is the primary source of official industrial statistics in India. The survey is conducted annually under the provisions of the Collection of Statistics Act. It covers all factories registered under the Factories Act, 1948, which includes all establishments using power and employing 10 or more workers and those not using power and employing 20 or more workers. The scope of the survey extends to the entire country except for the states of Arunachal Pradesh, Mizoram, Sikkim, and the union territory of Lakshadweep. The survey provides detailed information about income statement and balance sheet items, as well as employment details, material inputs, and output products and costs. Table 3 Panel B provides summary statistics for key firm variables.

4. Election Cycle in Bank Loans

4.1. Lending to Agriculture and Manufacturing Firms

Figure 2 gives preliminary evidence on the bank lending cycles. Using data on total bank lending in each district of 20 large states in India, I assign each district-year observation to one of the five bins: two years before an election, one year before an election, election year, one year past an election, or two years past an election.[11] Bank lending data is reported with a fiscal-year end date of March 31. For a fiscal year

[11] Data on aggregate bank lending at each district is available at the Reserve Bank of India website: https://www.rbi.org.in.

to be denoted as an election year at the state level, the state election should have been held after September 30th of the fiscal year and before October 1st of the next fiscal year. For each bin, I calculate the share of total credit given to the agricultural and manufacturing sectors. Clearly, the share of agricultural credit increases as an election approaches, whereas the share for the manufacturing sector falls. The agricultural sector received 10.4% of total bank credit two years before elections. The share increased to 12.1% during the election year. At the same time, the manufacturing sector's credit fell from 42.5% to 40.5%. Notice that the decrease in the manufacturing share roughly offsets the increase in the agricultural share.

To econometrically test for the existence of a political cycle, I use a specification similar to Cole (2009). I compare the amount of agricultural or manufacturing credit extended by a bank branch in an election year to the amount extended during non-election years. To control for macro-economic fluctuations and business cycles, I use region-year fixed effects. The RBI divides the country into six geographical regions, with a median of five states in a region. Using region-year fixed effects instead of year fixed effects allows different geographical regions to have different time trends. Hence, business cycles at the regional level do not drive my results. The regression specification can be written as:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta Election_{st} + \delta X_{st} + \varepsilon_{ist} \tag{1}$$

The dependent variable, y_{ist}, is log total credit extended by bank branch *i* in state *s* to either the agricultural or manufacturing sector in year *t*. $Election_{st}$ is a dummy that takes the value of 1 if state *s* had an election in year *t* or year *t-1*. Hence, the dummy takes the value of 1 in two of the five years in an election cycle. α_i denotes bank-branch fixed effects whereas γ_{rt} denotes region-year fixed effects. X_{st} controls for time-varying state-specific characteristics—the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Standard errors are clustered at the state level.

Although the constitution mandates state elections every five years, the incumbent government can call elections early. This option can bias the results if economic conditions drive the decision to call an early election. Fortunately, during the period of analysis, only 2 out of the 60 elections are early. These two elections constitute just 1.73% of our bank loan data.[12] To ensure that early elections do not bias the results, I drop these two elections from my analysis. All results hold when I include data from these two elections.[13]

[12] The two states – Goa and Manipur – are among the smallest Indian states and the manufacturing database does not cover Manipur. The two elections together constitute less than 1% of the manufacturing firm data.

[13] Alternatively, following Khemani (2004), I use as an instrument for election year a dummy, E_{st}^{IV}, that takes a value of 1 if four or five years have passed since the last election. Hence, the first stage is:

$$E_{st}^{IV} = \alpha_i + \gamma_{rt} + \beta Election_{st} + \delta X_{st} + \varepsilon_{ist}$$

In this first-stage regression, the estimated coefficient is 0.99 with a standard error of 0.01. The first stage explains 97% of the variation in election years, since early elections are rare in my sample. The results from OLS, reduced form and IV regressions (reported in Internet Appendix Table A1) are all similar in magnitude, statistically significant at the 5% level, and they all point to electoral cycle in credit.

If banks are forced to increase lending to the agricultural sector during elections, the coefficient on the election dummy should be positive when the dependent variable is total branch credit to the agricultural sector. Column 1 of Table 4 (Panel A) shows results from regression specification (1). Since the dependent variable is in log, we can interpret the point estimate as percentage change during elections. Bank credit to agriculture increases by 9.4% during election years. The point estimate is statistically significant at the 1% level.

Similarly, if banks reduce lending to manufacturing firms during elections, then the coefficient on the election dummy should be negative for the regression in which the dependent variable is total branch credit to manufacturing firms. The coefficient on the election dummy in column 2 implies that credit to manufacturing firms falls by 2.7% during the election years (statistically significant at the 5% level). In column 3, I test if aggregate bank lending increases during elections. Although the point estimate suggests that total lending is higher during elections, the coefficient is not statistically significant. Panel B repeats the same analysis, but restricting the sample to only those bank branches that lend to both agriculture and manufacturing. This ensures that the sample size remains constant across the specifications. The results are very similar to those in Panel A.

4.2. Where is Bank Credit Distorted More?

If political considerations drive the temporal variation in bank credit, then the size of the credit cycle should be larger where such a manipulation can influence the electoral outcome. For example, exerting effort in influencing banks to divert manufacturing credit toward agriculture makes little sense in election constituencies where a very small proportion of voters rely on agriculture. Similarly, increasing agricultural lending in a constituency where the election contest is not expected to be tight would not pay off—credit distortion would make no difference to the outcome of an election in such a constituency.

To test for such political motivations, I modify the basic regression specification to include an interaction term I_{ct} that proxies for whether the effect of credit manipulation on the electoral outcome in a constituency would be high or low:

$$y_{icst} = \alpha_i + \gamma_{rt} + \beta_1 Election_{st} + \beta_2 Election_{st} I_{ct} + \beta_3 I_{ct} + \delta X_{st} + \varepsilon_{ist}$$

In my first test, I_{ct} proxies for the closeness of the election in a constituency. Each constituency is assigned a dummy that equals 1 for the entire election cycle (three years before an election to one year after an election) if the incumbent local representative belongs to the ruling party, the ruling party's candidate either wins or comes in second in the subsequent election, and the victory margin in the subsequent election is less than 5% of total votes polled. Note that for the dummy to equal 1, I require that the incumbent local representative belongs to the party in power in the state. This is because regulatory provisions allow state governments to directly influence bank lending at the branch level. Next, I map each bank branch to the election constituency, using the branch address and GIS software.[14] Thus, the dummy denotes whether the bank branch was located in a constituency that had a close election contest.

Table 5 presents results from this analysis. In panel A, I analyze agricultural credit whereas in panel B, I analyze manufacturing credit. Consistent with the notion that increased agricultural lending is the result of political influence on banks, I find the lending cycle is larger in constituencies that had a closely contested election. Column 1 shows that bank branches in constituencies with close electoral competition increase their agricultural lending by 5.3 percentage points more than branches in other constituencies. Similarly, column 4 suggests that constituencies with close elections reduce their lending to the manufacturing sector by 4.9 additional percentage points compared to constituencies that did not have a fiercely fought election. Thus, not only do we find temporal fluctuations in bank credit that perfectly align with election cycles, but we also find that the fluctuations are much more pronounced when incentives to manipulate voters via bank loans are greater. In results not reported, the interaction term becomes economically small and statistically significant only at the 10% level when I relax the requirement that the incumbent elected representative at the constituency belong to the party in power at the state level. This suggests that an incumbent needs to be aligned with the party in power at the state in order to influence bank lending in her constituency.

To further strengthen the assertion made in this paper—politicians influence banks to lend more to the agricultural sector during elections for electoral gains—I exploit heterogeneity across constituencies in the distribution of voters who rely on agriculture for their livelihood. Per data from the 2001 census, 73.3% of the rural and just 7.9% of the urban workforce was engaged in agriculture.[15] If politicians trying to win farmers' votes drive my results, we should find stronger results in locations where farmers have more "political weight".

To perform this test, I redefine the interaction dummy I_{ct} such that it takes a value of 1 if the bank branch was located in a rural area and 0 otherwise. The dummy, I_{ct}, hence is defined at the bank branch level for this analysis. The test examines whether the effect of elections on bank lending is equally strong for branches located in rural and urban areas. The rural classification for a branch is time-invariant and hence the direct effect gets absorbed in branch fixed-effects. As columns 2 and 4 show, the jump in agricultural credit during the election years is 14.2 percentage points more in rural locations than in urban locations, whereas the drop in manufacturing credit during the election years is 2.4 percentage points more in rural locations than in urban locations. Hence, politicians strategically direct more agricultural loans in locations where such a move would endear a larger proportion of voters. Notice that the results are not mechanical. Bank branches in rural locations do lend a higher share of their total credit to the agricultural

[14] Election data and the mapping from branch address to corresponding electoral constituency are not comprehensive, leading to a lower sample size for this analysis.

[15] The census uses a combination of population, population density and proportion of male working population engaged in agriculture to determine whether a location is urban or rural.

sector. However, the above test indicates that a branch located in a rural area *increases* its agricultural lending during an election by a greater *percentage point* than a branch located in an urban area.

The rural vs urban classification is a binary measure that absorbs a lot of variation across locations in terms of the share of workforce engaged in agriculture. To get more insight, I directly measure the share of workforce engaged in agriculture in each *Tehsil*, which is equivalent to a sub-district.[16] I map each branch location to the *Tehsil* in which it is located. The downside of using this measure is that a *Tehsil* is much larger in size than the smallest administrative unit defined in the bank database—the level at which rural vs urban is defined.

In columns 3 and 6, I interact the election dummy with the share of workforce engaged in agriculture in the *Tehsil* in which a bank branch is located. The point estimate on the interaction term in column 3 is positive and significant at the 5% level. The average share of workforce engaged in agriculture in a Tehsil is 0.67, with a standard deviation of 0.21. Hence, a one standard deviation increase in the share of agricultural workforce increases the size of the agricultural lending cycle by approximately six percentage points. Similarly, using the point estimate from column 6, a one standard deviation increase in the share of agricultural workforce reduces lending to manufacturing firms by approximately an additional one percentage point.

4.3. What Causes Substitution and Crowding-Out?

The findings in this section lead to an important question. Why do bank branches need to cut their manufacturing lending when they are forced to increase their agricultural lending outlay? It should be noted that this paper studies state elections, and not national elections. For a national bank with branches all over the country, state elections do not cause an aggregate lending shock—there are elections every year. Lending shocks are rather local in nature, with different states holding elections in different years and hence branches located in different states requiring increased agricultural lending at different times. In a perfectly functioning internal capital market for the banking organization, local shocks (increased agricultural lending in election states) should get smoothened out, i.e. we should not find local crowding-out effect in other sectors. The results, thus, suggest there are constraints that lead to crowding out at the branch level. For example, branches might be constrained in how much credit they can disburse each year. They could also be constrained in expanding their loan processing capacity (labor, technology etc.). Chakraborty et al. (2014) show that banks in the United States that had considerable branch presence in locations that witnessed strong real estate price appreciation during 1998-2006 increased their mortgage lending at the expense of commercial lending (lending to firms). They argue that the crowding out is caused by credit or

[16] Data on workforce at the Tehsil level is obtained from the 2001 census.

organizational constraints faced by banks. In this section, I show that shorter distance between a bank-branch and the headquarter seems to alleviate these constraints.

A perfectly functioning internal capital markets should be able to overcome local constraints. However, agency costs between branch officers and the headquarters could make the functioning of internal capital markets difficult. Stein (2002) argues that soft information might not be credibly transmitted in a hierarchical banking organization. Consistent with this view, Sapienza (2002) finds that loans with more soft information are less likely to be issued by banks subsequent to merger that tend to make them more hierarchical. Liberti and Mian (2009) find that greater geographical distance between the information collecting agent and loan approving officer reduces the reliance on soft information.

In order to test if this information channel plays a role in the crowding out effect, I collect data on the bank's organizational structure. The bank's domestic operations is divided into 37 regions, each with its own regional head-office. If the regional headquarter has to approve any substantial increase in a branch's lending capacity, a shorter physical distance between a bank branch and its regional headquarter could facilitate the flow of soft information and alleviate agency problems that lead to crowding out. Branch managers closer to the headquarter might also have better relationship with and more influence over decision makers in the zonal headquarter.

In Table 6, I examine how branch lending around elections varies with branch's distance from the regional headquarter. We have to be careful about one confounding effect: the regional headquarters are in big urban cities, and consequently branches very close to the headquarter are likely to be urban branches. To avoid any confounding effect, I restrict my analysis to rural branches and compare rural branches located relatively closer to the regional headquarters to those located far away from the headquarter.

In Panel A, I examine whether rural branches located closer to regional headquarters are otherwise similar to rural branches located far away from the headquarters. I divide the entire population of rural bank branches into two groups based on their distance from their respective regional headquarter. The two groups seem similar in the size of their lending books. Branches closer to the headquarters lend just a fraction more to agriculture than those located far away. Both groups lend almost similar fraction to the manufacturing sector. In short, the two groups look pretty similar in their lending behavior.

In Panel B column 1, I analyze how the election cycle in agricultural lending varies with distance from regional headquarters. The point estimate on the interaction term is negative, but not statistically significant. Hence, branches are exposed to similar political pressure to increase agricultural lending around elections, irrespective of their proximity to the regional headquarter. In column 2, I examine lending cycle in manufacturing sector. The coefficient on the interaction term is negative and statistically significant at the 5% level. Branches located far away from the regional headquarters cut their manufacturing lending by an additional 3.3 percentage points during elections than those closer to the headquarters. Hence, although branches on an average increase their lending to agriculture during elections equally irrespective of their distance from the headquarter (if anything, those closer seem to increase their agricultural lending more during elections), the ones far away from the decision makers cut down more on their lending to manufacturing firms. This suggests that the crowding out is more prominent for branches located far away from the decision makers.

In column 3, I examine total branch lending. Consistent with the evidence in columns 1 and 2, I find that the increase in total branch lending during elections is more for branches closer to the regional headquarters—these branches can increase their agricultural lending with relatively weaker negative impact on their lending to the other sectors. Overall, the evidence suggests that closer distance between a branch and the regional head-office alleviates constraints that lead to crowding-out.

4.4. Credit Distortion and Loan Performance

If additional credit to farmers during an election is politically motivated, this additional lending could affect loan performance. To test this hypothesis, I estimate the relationship between agricultural loan performance and the election cycle. To measure agricultural loan performance, I use the share of agricultural credit late at each bank branch. A loan is considered late if it is past due for more than ninety days. Most agricultural loans are short-term credit, expected to be repaid after the growing season. Hence, bad lending decisions should lead to worse loan performance fairly quickly.

If additional agricultural credit during an election increases the share of bad loans, we expect the coefficient on the election dummy to be positive. The results are presented in Table 7. In column 1, I test the performance of agricultural lending. The dependent variable is the share of total agricultural credit late at a bank branch (i.e. agricultural credit late in payment/ total agricultural credit). The regression coefficient suggests that the share of agricultural loan late increases by 1.3 percentage points during an election. On an average, 15.8% of agricultural credit is late during the off-election years. Hence, a 1.3 percentage point increase suggests that the share of late credit goes up by 8.6%.

Does the election cycle affect performance of manufacturing loans? If election causes a general slowdown in economic activity, then the manufacturing loan performance could worsen during an election. On the other hand, if the observed fall in manufacturing credit during an election is supply-driven, then there is no reason to expect deterioration in manufacturing loan performance. In addition, if banks decide to cut their marginal loans when forced to reduce aggregate lending to manufacturing sector, one might even see an improvement in average loan performance during elections. Ideally, we would want to track loans over time and analyze performance of loans originated during elections against those originated during off-election years. Unfortunately, my dataset does not allow me to see when a particular loan was originated. Hence, we need to be cautious while drawing inferences from the analysis of manufacturing loan performance.

In column 2, I analyze how the share of manufacturing credit late varies with elections. The coefficient on the election dummy is negative but significant only at the 10% level. The point estimate suggests that the share of manufacturing loan late falls by 0.3 percentage points during an election. On an average, 8.1% of manufacturing credit is late during the off-election years. Hence, the share drops by 3.5% during the election years. It is safe to say that manufacturing loan performance does not deteriorate during elections.

Figure 3 plots variation in loan performance over an election cycle. For this analysis, I replace the election dummy with a set of indicator variables, where each variable denotes the number of years to the next election. The election year is the omitted category. I plot the coefficients in the figure. We can see that agricultural loan performance peaks three years before an election. Performance is equally bad during the election year and the year before—closely tracking the trend in lending.

To summarize, the set of evidence provided in this section clearly establishes the causal relationship between state elections and an increase in agricultural credit as well as a reduction in manufacturing credit. The evidence on variation in size of the credit cycle with the closeness of election and with voters' dependence on agriculture suggests that the cycle is politically motivated.

5. Real Effects on Firms

A temporary fall in the availability of bank loan to manufacturing firms would be of little concern if firms could ride it out with ease. In this section, I study how firms adjust to temporal variation in the availability of bank credit. I examine whether firms are forced to alter their real decisions, and whether such alterations lead to significant costs. On one hand, if the election schedule is pre-determined and firms are able to plan ahead, the real effects might be limited. On the other hand, if adjustments are costly, this election-induced credit cycle might produce significant real effects. To perform this analysis, I use detailed firm-level data available from the Annual Survey of Industries. I begin with univariate analysis of variation in firm leverage with elections. I then perform a multivariate regression that controls for variables that could directly influence the dependent variable. After confirming that the variation in firm leverage over the election cycle is consistent with the bank lending cycle that we found in the previous section, I move on to examine how firms adjust to this election-induced credit squeeze. With an array of results at our disposal, I conclude this section by ruling out alternative explanations for the results.

5.1. Firm Leverage around Elections

Figure 4 plots trends in firm leverage. I assign each firm-year observation to one of the five bins: two years before an election, one year before an election, election year, one year past an election, or two years past an election. For each bin, I calculate the median firm leverage. The figure shows that median leverage in election year is 3.3% lower than median leverage two years after election.

To control for time-varying macro and local economic conditions, I use a regression specification similar to equation (1). In addition to region-year fixed effects, I also include two-digit industry-year fixed effect, μ_{kt}. This allows different industries to have their own time trend. To account for local economic conditions, I use state GDP growth as an additional control variable (X_{st}). The regression specification can be written as:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta Election_{st} + \delta X_{st} + \varepsilon_{ist} \tag{2}$$

where *i* denotes firm, *s* denotes state, *t* denotes time, and *k* denotes the two-digit industry code. The dependent variable is in log. As before, the coefficient on the election dummy can be interpreted as the percentage change in the dependent variable when the dummy equals one.

Table 8 shows results from this analysis. In column 1, I examine whether elections affect firm leverage. Leverage is defined as total outstanding debt scaled by the beginning of year book value of total assets. The coefficient on *Election* dummy captures the effect of election on firm leverage. Leverage is 2% lower during the election years. This is comparable to the 2.7% drop in bank lending to the manufacturing sector that we found in the previous section. Hence, the reduction in credit outlay to manufacturing firms is reflected in the leverage these firms exhibit.

If this drop in firm leverage is the result of lending distortion caused by political interference, then firms located in places where political interference on banks is high should experience a larger drop in leverage. As argued before, political pressure to increase agricultural lending is expected to be higher in places where a significant proportion of voters rely on agriculture for their livelihood. Hence, I interact the election dummy with the share of workforce engaged in agriculture in the district where the firm is located.[17] If the fall in leverage is caused by political interference on bank lending, then the coefficient on the interaction term should be negative, implying a higher interference in places where more voters rely on agriculture for their livelihood. Column 2 provides the results. The coefficient on the interaction term is negative and statistically significant. The average share of workforce engaged in agriculture is 0.61, with a standard deviation of 0.19. Hence, the estimate implies a one standard deviation increase in the share of agricultural workforce reduces firm leverage in the election years by approximately an additional one percentage point.

5.2. Do Firms Use Up Cash Reserves?

How do firms respond to this squeeze in bank credit? The first line of defense comes from cash on the balance sheet. The precautionary savings motive of cash holdings argues that firms can use their cash

[17] To protect firm identity, the database does not provide the address of firm. I only know the district in which a firm is located.

reserves to finance their activities when other sources of funding are not available. Opler et al. (1999) find strong evidence among US firms for the precautionary savings motive behind their cash holdings. In addition, Faulkender and Wang (2006) report that the value of cash is greater for constrained firms than for unconstrained firms, highlighting the precautionary savings motive of cash holdings.

In column 1 of Table 9, I test if firms use up their cash reserves during elections. The dependent variable is cash on the balance sheet scaled by lagged book value of total assets. Firms seem to build up their cash reserves during good times and run them down during the lending draught to fund their day-to-day operations. The coefficient on the election dummy is negative and statistically significant at the 5% level. The estimate suggests firms hold 2% less cash during elections.

5.3. Impact on Investment

In column 2 of Table 9, I examine how the lending squeeze affects firms' investment decisions. The dependent variable is logarithm of firm investment scaled by the lagged book value of total assets. The point estimate on the election dummy is negative and is statistically significant at the 5% level. The result suggests investment during election years is 3.6% less than that in non-election years. Since investment is lumpy, predicting whether firms are actually forgoing investment opportunities is difficult. Nevertheless, at the minimum, firms are forced to delay investment.

Lumpy investment also makes using a log specification undesirable. Doms and Dunne (1998) find that 25% to 40% of an average plant's cumulative investment over 17 years is concentrated in a single year. Whited (2006) argues that external finance constraints lower a firm's probability of undertaking a large project today as a function of the time since last project, thereby making investment more intermittent for such firms. If firms do not invest every year, we lose important information about firm investment by dropping observations where investment equals 0. Hence, in column 3, instead of a log specification I use investment scaled by the lagged book value of total asset as the dependent variable. Hence, the coefficient on the election dummy now measures change in the level of scaled investment during the election years (and not the percentage change). The point estimate is again negative and statistically significant. Scaled investment is 0.3 percentage points lower during the election years compared to the off-election years. Average scaled investment during the off-election years is 7.6%. Hence, the regression result suggests that investment during the election years is 3.9% less than that in off-election years—comparable to the estimate from column 2.

5.4. Impact on Employment

Availability of external finance could also affect firms' employment decisions. Firms must finance labor payments during the production process. Additionally, because firms need to finance working capital during the production process, a fall in the ability to finance working capital could lower production. A lower production scale should require employment to be adjusted accordingly. Pagano and Pica (2012) provide evidence that during banking crises, employment grow less in the industries that are more dependent on external finance. Using three 'quasi-experiments', Benmelech et al. (2011) show that financial constraints and the availability of credit play an important role in firm-level employment decisions.

In this subsection, I examine if firms reduce their employment levels during the election years. I use specification (2) where the dependent variable is the logarithm of the number of employees scaled by the lagged firm size. The results of the analysis are provided in Table 10. Column 1 analyzes temporary workers of firms. Employment of workers on temporary contracts falls by 3.3% during the election years. In column 2, I analyze permanent workers of firms. Employees with permanent jobs do not see any change in employment. Firing permanent employees is especially difficult in India, given its restrictive labor laws. The point estimate indicates that employment of permanent workers increases by 0.6% during the election years. However, the coefficient is statistically insignificant. The overall effect is an economically and statistically significant 1.2% drop in total employment during the election years (column 3). The fact that firms fire temporary workers makes sense. The election cycle is pre-determined and its effects are anticipated. Firms understand normal credit flow will be restored following this temporary credit squeeze. Temporary workers provide firms the flexibility to adjust their payrolls and labor workforce dynamically. Moreover, these workers are more likely to have been hired for jobs that require less firm-specific knowledge and training. Hence, the overall cost of hiring and firing such workers is less.

An alternative interpretation of this result could be that elections increase the demand for workers outside manufacturing (presumably for election campaign and support). As a result, temporary workers leave their jobs. However, it seems far-fetched to believe that the demand for such workers for election-related activities would last for two years (remember that our election indicator takes the value of 1 both during the election year and the year before election). Second, election-related activity would unlikely lead to such a large-scale exodus of workers. Third, I directly examine employee wages to see whether the drop in payroll count also leads to an increase in wages earned by employees.

In column 4, I examine how contract-employee wages vary along an election cycle. Wages are calculated as total compensation scaled by total number of man-days. The point estimate suggests a statistically insignificant 0.3% increase in wages of contract workers during the election years. Similarly, columns 5 and 6 analyze wages of permanent workers and wages of all workers, respectively. We see little movement in wages earned by either category of workers. Hence, firms do not seem to be making any effort toward retaining these workers.

For politicians to support policies that lead to job losses in the manufacturing sector, the political cost should be limited. I perform a back-of-the-envelope calculation for the number of workers laid-off.

During the 1999-2008 period, firms in the dataset employed a total of 1,578,198 contract workers per year on an average. If firms fire 3.3% of their contract employees during an election, this percentage translates to around 10,400 jobs lost every year due to elections. Although this is a significant number in terms of jobs lost, it is still a very small number in political calculations. There are 4120 election constituencies and on an average one-fifth of them go to election every year. So, roughly 13 manufacturing jobs are lost per election constituency—not a significant number given an election constituency on an average had 179,000 voters as per the 2001 census.

5.5. Production and Factor Utilization

Firms need financing to support production and investment. When hard pressed for external sources of finance, firms are left with two options: (i) substitute external finance with internally generated cash, and (ii) cut down production and investment. Results from previous sections show that firms run down their cash reserves and reduce their investments. If the reduced availability of bank loans leads to a shortage of working capital, this shortage could also affect a firm's production.

To trace down variation in firm's production over an election cycle, I use a modified version of regression specification (2). In particular, I trace out the co-movement by replacing the election indicator with a set of dummies, each representing the number of years to the next scheduled election. I use the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta_{-j} Election_{st}^{-j} + \delta X_{st} + \varepsilon_{ist}$$

where $Election_{st}^{-j}$ equals 1 if the next scheduled election is in j years for state s at time t. Election year is the omitted category, implying the coefficients β_{-j} should be interpreted as the percentage change from the election year.

Table 11 presents results from this regression. In column 1, I examine how the production scale varies over an election cycle. Compared to the election year, output in terms of value added is 2.9% higher two years before an election. This finding suggests firms are forced to cut down production during elections. Of course, this fall in production could also be demand driven. Using evidence from product prices and actual sales, I argue in Section 5.6.1 that the fall in production is not demand driven.

Next, I examine the effect of lower production during elections on plant utilization levels. Businesses change their demand for inputs more slowly than the shocks to input demand warrant (see, for example, Hamermesh and Pfann (1996)). The incentive to tone down adjustments to factor inputs is even higher for a temporary shock, because inputs have to subsequently be brought back to their original levels. To the extent that firms cut down their production without adjusting factor inputs accordingly, factor utilization will fall.

As a first step, I analyze how value added as a fraction of capital stock and value added as a fraction of labor input varies along the election cycle. In column 2, I use log value added as a fraction of capital stock as the dependent variable. The trend is similar to the trend in production. Two years before an election, firms produce 3% more as a fraction of their capital stock than they produce in the election year. This behavior seems reasonable. Fixed assets are indivisible—adjusting capital stock in a piecemeal manner is not always possible. Furthermore, the temporary nature of the shock makes selling assets during elections less worthwhile even when piecemeal adjustment to stock is possible, because capital stock will have to be replenished post-elections. Had this been a permanent shock, it would make more sense for firms to adjust down their capital stock in a timely manner. In column 3, I analyze value added as a fraction of labor compensation. The size of the cycle is smaller than in column 3, consistent with the notion that adjusting capital is more difficult than adjusting labor. This is in line with the employment results—firms cut their temporary workers during elections.

How does one interpret these value added ratios? To get some insights, I assume a Cobb-Douglas production function of the following form:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s}$$

where Y_{si} is the output (value added) of firm *i* in industry s, K_{si} is the amount of accumulated capital, L_{si} is the amount of labor and A_{si} denotes total factor productivity (tfp). α_s denotes elasticity of output with respect to capital while β_s denotes elasticity of output with respect to labor. I assume these elasticities are constant within an industry. My analysis of production along an election cycle has nothing to say about a firm's production technology (total factor productivity), which is slow-moving and should not react sharply to election-induced credit squeezes.[18]

From this production function, we can calculate the marginal revenue product of capital (*mrpk*) and the marginal revenue product of labor (*mrpl*) for each firm each year as follows:

$$mrpk_{si} \propto \alpha_s \frac{P_{si} Y_{si}}{K_{si}}$$

$$mrpl_{si} \propto \beta_s \frac{P_{si} Y_{si}}{L_{si}}$$

To the extent that α_s and β_s are constant within an industry, we can interpret the dependent variables in column 2 and 3 as the marginal revenue product of labor and capital, respectively. Thus, one cost of election-induced lending distortion is a fall in factor utilization, because firms produce less for the

[18] Of course, some general equilibrium effect of election-induced inefficiencies on a firm's decision making will exist that could affect the level of tfp.

given level of capital and labor. The fact that *mrpl* also falls indicates firms are unable to cut their labor force to the full extent, probably because of labor regulations.

As a robustness check, I replace capital stock with a measure of capital services flow. The productivity literature has long focused on the role of pro-cyclical capacity-utilization rates for inference regarding cyclical movements in labor productivity. Burnside, Eichenbaum, and Rebelo (1995) use industrial electrical consumption to measure capital services. Following their lead, I replace capital stock with energy consumption. Column 4 reports results from this regression. Reassuringly, the cyclical variation in the marginal revenue product of capital vanishes, confirming the notion that cyclical capacity-utilization levels drive variation in *mrpk*. Conditional on the amount of energy consumed, firms produce as much in election years as they do in non-election years.

The set of evidence in this sub-section suggests that a squeeze in the availability of bank credit forces firms to reduce their scale of production. To support working capital, firms run down their cash reserves and cut investments. In line with lower production, firms trim their workforces; adjustment costs and the temporary nature of shock do not allow firms to cut their workforces to a level suggested by the marginal productivity measures. Adjustment costs are much greater for fixed capital. Hence, for a given level of labor and capital, firms produce much less than they could have produced without constraints on their working capital.

5.6. Alternative Explanations for Election Cycle

My regression specification allows me to make a causal inference about the impact of elections on firms. In addition, staggered state elections help me rule out explanations based on macro-economic factors that might be driven by elections. Still, alternative explanations for the results are possible. In this subsection, I discuss these explanations and provide results that help me rule them out.

5.6.1. Fall in Demand

Elections are known to affect the economy, either via direct policy interventions by the ruling incumbent or indirectly due to uncertainties and delays in bureaucratic decision making. A fall in demand for manufacturing goods brought about by a sluggish local economy can explain a fall in production and the availability of bank funding. However, this line of reasoning has two important predictions. First, a fall in production driven by sluggish demand predicts a fall in product prices. In column 1 of Table 12, I examine how prices vary over an election cycle. The unit of measurement is firm-product-year. The dependent variable is the product price and I allow for secular time trends in the prices of the five-digit product codes across firms. Hence, the identification comes from analyzing how the price of a firm's product changes along an election cycle after controlling for aggregate time trend in the price of that product category.

Instead of a fall in prices as predicted by an explanation involving sluggish demand, I find an increase in the prices during an election year. Prices are around 4% higher in an election year. Because firms are forced to operate at a suboptimal scale, they face higher average costs and seem to be passing on some of these costs to their customers.[19] It is unlikely that firms would increase prices if the fall in production was triggered by a sluggish demand for goods.

Furthermore, the direct effect of sluggish demand should be on sales—and then a trickle-down effect on actual production. In column 2 of Table 12, I examine how sales vary along an election cycle. The cycle in sales is not only economically small, but also statistically insignificant.[20] The fact that the actual sales cycle is muted supports the argument that fall in production is not driven by a fall in demand. Both the fall in production and the increase in prices are more consistent with our preferred credit squeeze explanation.

5.6.2. Political Uncertainty

Political uncertainty can also affect firm's decision making. The possibility of a policy change post-election makes it worthwhile for firms to delay actions whose effect on firm value depends on the choice of government policy. Studying national elections around the world, Julio and Yook (2012) show that firms reduce investment expenditure in election years. Although I too find a significant reduction in investment expenditure during elections, I also find an accompanying fall in leverage and cash holdings. Jool and Yook (2012) instead find that firms increase their cash on the balance sheet, and attribute their result to precautionary holdings. If our results were entirely driven by uncertainty, firms should have hoarded their cash reserves instead of using them up before elections.

Cross-sectional analysis further supports our proposed explanation. Table 13 provides results on heterogeneity tests of the effect of elections on firm leverage. In column 1, I test whether the effect of elections is different for firms located in rural versus urban locations. I find a fall in leverage in rural locations—where a larger share of voters rely on agriculture for livelihood—but not in urban locations. Additionally, I show in column 2 that the decrease in firm leverage is economically and statistically significant for private firms but not for publicly traded firms. Traded firms have lower information asymmetry, making them less reliant on their local bank branch for bank funding. They also have multiple relationships with a bank, including for investment banking services. As a result, they are more likely to bank directly with the headquarters and not be constrained by local lending shocks.

5.6.3. Other Explanations

[19] Firms are assumed to have a fixed cost component.
[20] This implies that firms use up their inventory of semi-finished and finished goods.

Elections could affect the economy in other ways that could improve the prospects of agricultural firms and/or deteriorate the prospects of manufacturing firms. However, any alternative hypothesis has to explain why increased agricultural lending and reduced manufacturing sector lending during elections are more prominent in areas where farmers have more political weight. Could it rather be the case that politicians cater to farmers during elections via other channels? Such catering would be higher where farmers have more political weight. However, if increased agricultural lending is in response to improved prospects of farmers due to political catering, and not because of direct political interference in the banking sector, loans disbursed during elections should not perform worse. Overall, the set of evidence is more consistent with a politically influenced bank lending channel. Any other explanation would have difficulty rationalizing all our findings.

5.7. Cost to Manufacturing Sector

In this paper, I study a partial equilibrium effect—how firm activity during the election year is different from activity during the off-election years. Because I do not see the counter-factual world where states do not hold elections, I cannot determine whether overall investment, production, or employment over a five-year election cycle is lower because of the lending distortions. Nevertheless, I show that lending distortions affect real decisions of firms—they do cut back on their investment, employment and production during elections. However, one could argue that what we lose during the election years is recouped during the non-election years so that there is no net loss over the election cycle.

I argue that the fall in plant-utilization level during election has significant cost that cannot be 'compensated for' during the off-election years. If plants leave productive capacity idle during elections because of funding constraints, this idle capacity cannot be used later. Plants cannot really make up for the inefficient production during elections. Hence, less efficient production during elections is a direct cost of political interference on firms.

I perform a back-of-the-envelope calculation to estimate the cost on the manufacturing sector. I assume that the average utilization rate during the three off-election years (three years before election, two years before election and one year before election), when production is not constrained by credit, represents the *normal* utilization rate. I then calculate the *hypothetical* increase in production if plants operated at normal utilization level during the election years as well.

In Table 14, I compare the utilization rate during the two years when production is affected because of elections to the rate during these off-election years. Column 1 presents results from this analysis. The coefficient on *Election* dummy is −0.019, and is statistically significant at the 1% level. Hence, for a given level of fixed capital, firms produce 1.9% less during elections. The effect of credit squeeze on production efficiency might not be uniform across all firms. One might worry that the adverse effect on utilization rates is limited to smaller firms that do not contribute much to aggregate production. To test this, I sort firms into three bins based on their sales, capital stock, or the total number of employees. To alleviate the concern that the result in column 1 might be driven by small firms, I exclude firms in tertile 1 of each sort and repeat the analysis in columns 2, 3 and 4. For each specification, I find that the point estimate is comparable to the estimate obtained in column 1, indicating that the result obtained in column 1 is not exclusively driven by small firms.

The estimate from column 1 suggests that using the same amount of fixed capital, firms could have produced 1.93% more during an election had there been no funding constraint. Using data from the Planning Commission of India, I find that the manufacturing sector's average contribution to GDP during the 1999-2008 period was 27%. Hence, the manufacturing sector could have added another 0.20% to the country's GDP (election affects two out of five years of an election cycle) in the absence of political interference. The estimates are slightly higher when I allow for heterogeneous effect on firms based on their size as measured by sales, capital stock or number of employees (point estimates are reported by tertile group in columns 5, 6 and 7). My calculations suggest that the manufacturing sector would have added another 0.37%, 0.23%, and 0.24%, respectively, to India's GDP in the absence of distortions to bank credit.

A few caveats are in order. The estimates above come from 'aggregating' up a partial equilibrium effect. We do not see the capacity-utilization rates in a counter-factual world with no elections—the assumption about the *normal* utilization level is subjective and the calculated aggregate cost depends on this assumed level. However, the paper provides an array of tests that clearly show that the utilization levels are lower during elections, and the drop in utilization rates is equally strong for larger firms that matter more for aggregate industrial production. Because the manufacturing sector constitutes a considerable fraction of the economy, even a small drop in production efficiency could have a significant impact on the country's GDP.

One should also be careful about interpreting the factor utilization results in terms of increased GDP. This is really a result about loss of production efficiency. In the absence of election induced lending distortions, firms would produce their goods more efficiently, choosing an optimal mix of fixed capital and labor. Consequently, firms would produce the same amount of goods with less fixed capital. Increase in GDP requires additional assumptions about demand and production, and about the ability to use the spare resources in an equally efficient manner.

6. Conclusion

A growing literature examines how political favors arise through the banking sector in the form of cheap and preferential lending to particular groups of borrowers. However, very little is known about the real cost of such distortions. In this paper, I have examined one particular real cost of political interference in the banking sector: when banks are forced to increase lending to certain sectors or groups of borrowers, other productive sectors of the economy get crowded out. This crowding out has a significant cost. I show lack of bank funding forces manufacturing firms to scale down production and lay off temporary workers. Reduced production during elections lowers plant utilization rates and renders some productive capacity idle. The findings are important—they show that the costs of such political interference permeate well beyond the banks that are forced to make these favorable loans.

A broader takeaway from this paper concerns productivity and economic growth. My findings connect to the micro and macro literature that compares productivity differences across firms in different economies. Huge differences in output per worker between developed and developing countries has been largely attributed to differences in efficiency with which factors of production are used (Howitt (2000), Klenow and Rodriguez-Clare (2005)). Resource misallocation, including differential access to bank loans, can play an important role in explaining these differences in efficiency (see, for example, Hsieh and Klenow (2009)). The evidence in this paper provides an example of such misallocation. By fixing such distortions in the banking sector, we might be able to put resources into more productive use.

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Table 1: Credit Outlay by Industry

This table uses credit data from all commercial banks in India. Each row represents the share of total banking sector credit outlay to an industry group during the 1999-2008 period. Shares are calculated separately for public and private banks. In addition to public and private banks, there are numerous small regional rural banks and cooperatives.

	Public Banks	Private Banks
Agriculture	0.12	0.15
Manufacturing	0.42	0.36
Services	0.05	0.07
Personal	0.16	0.26
Trade	0.13	0.08
Others	0.12	0.09
Total	1.00	1.00
Share of total banking sector outstanding loan	0.72	0.10

Table 2: Distribution of Elections (1999-2008)

This table shows the distribution of state elections by year. Elections are staggered, with each state following its own five-year cycle. Elections in different states in a given year can happen at different dates/months—all state elections do not have to occur on a fixed date in a year.

Year	# of state elections	Year	# of state elections
1999	6	2004	6
2000	5	2005	3
2001	4	2006	4
2002	7	2007	7
2003	9	2008	9

Table 3: Summary Statistics on Branch Loan and Firm Data

Panel A contains information on variables used for bank branch lending analysis. This data is available for the 1999-2007 period. The unit of observation for lending data is branch-year. There are a total of 23,252 branch-year observations during this period. Not every bank branch lends to both the agricultural and manufacturing sector. A loan is considered late if principal or interest payment is 90 days overdue. Share loan late is calculated as a fraction of the total outstanding amount for each branch-year observation. Election year is a dummy variable indicating a state election in a given year. Panel B contains information on firm data obtained from the Annual Survey of Industries. This data is available for the 1999-2008 period.

	Mean	Standard Deviation	N
Panel A: Bank branch lending analysis			
Branch lending data:			
Log total credit	16.513	1.941	23,252
Log agricultural credit	14.538	1.474	15,380
Log manufacturing credit	15.531	2.249	22,523
Share agricultural loan late	0.157	0.295	15,380
Share manufacturing loan late	0.081	0.171	22,523
Election data:			
Election year	0.204	0.403	23,252
One year to election	0.204	0.403	23,252
Two years to election	0.216	0.411	23,252
Three years to election	0.207	0.405	23,252
Four years to election	0.170	0.376	23,252
Panel B: Firm analysis			
Log total assets	17.826	2.239	136,508
Debt/TA	0.346	0.463	105,416
Sales/TA	1.717	1.467	117,683
Value Added/TA	0.33	0.348	108,196
Cash/TA	0.038	0.063	135,225
Investment/TA	0.068	0.112	137,900
Employee Compensation/Sales	0.102	0.207	117,502

Table 4: Bank Lending Cycle

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta_1 \text{Election}_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes bank branch, *s* indexes state and *t* denotes time. The dependent variable is the amount of credit in log. Column 1 uses agricultural credit, column 2 uses manufacturing credit, while column 3 uses total credit. Election_{st} is an indicator variable that takes value of 1 in an election year and the year before an election. γ_{rt} is region-year fixed effects. X_{st} controls for time-varying state-specific characteristics—the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Panel A contains the full sample of branches. Panel B restricts the sample to branches that lend to both agriculture and manufacturing. The point estimates and standard errors are multiplied by 100.

Panel A: Full Sample

	Agriculture	Manufacturing	Total
	(1)	(2)	(3)
Election	9.45***	-2.74**	1.86
	[2.71]	[1.09]	[1.63]
Branch Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	15,380	22,523	23,252
R-squared	0.73	0.91	0.91

Panel B: Restricted Sample

	Agriculture	Manufacturing	Total
	(1)	(2)	(3)
Election	8.18***	-2.32**	1.69
	[2.48]	[1.08]	[1.93]
Branch Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	14,453	14,453	14,453
R-squared	0.75	0.85	0.86

Table 5: Where is Bank Credit Distorted More?

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta_1 \text{Election}_{st} + \beta_2 \text{Election}_{st} * I_{it} + \beta_3 I_{it} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes bank branch, *s* indexes state and *t* denotes time. The dependent variable is the amount of credit in log extended to either the agricultural sector (Panel A) or manufacturing sector (Panel B). Election_{st} is an indicator variable that takes value of 1 in an election year and the year before an election. I_{it} is the interaction variable: Close in columns 1 and 4, Rural location in columns 2 and 5, and the Share of workforce engaged in agriculture in columns 3 and 6. Close takes the value of one in an election where the victory margin at the constituency is less than 5%. Voters elect local representatives at the assembly constituency (a state has 137 constituencies on an average). The closeness of an election is therefore defined at the constituency level. I map each bank branch to the assembly constituency where it is located. A branch location is classified as rural or urban based on census 2001 data. According to the census, 52% of the rural and just 5.7% of the urban workforce was engaged in agriculture. The share of workforce engaged in agriculture is measured at the sub-district (Tehsil) level. Rural classification and the share of workers engaged in agriculture are time-invariant and hence get absorbed in branch-fixed effects. γ_{rt} is region-year fixed effects. X_{st} controls for time-varying state-specific characteristics—the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

Panel A: log(Agricultural Credit)			
	(1)	(2)	(3)
Election	5.82**	2.11	-6.24
	[2.66]	[3.72]	[7.68]
Election x Close	5.34**		
	[2.40]		
Election x Rural		14.23**	
		[5.07]	
Election x			29.13**
Share of workforce engaged in agriculture			[14.07]
Close	-1.08		
	[3.13]		
Branch Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	14,578	15,380	14,960
R-squared	0.73	0.74	0.74

Table 5: Where is Bank Credit Distorted More? (continued)

Panel B: log(Manufacturing Credit)			
	(4)	(5)	(6)
Election	-1.19	-1.80	-0.91
	[1.42]	[1.26]	[1.84]
Election x close	-4.90**		
	[2.06]		
Election x rural		-2.43**	
		[1.03]	
Election x			-3.79**
Share of workforce engaged in agriculture			[1.40]
Close	3.63		
	[4.02]		
Branch Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	21,207	22,523	21,550
R-squared	0.92	0.92	0.92

Table 6: Distance from Regional Headquarters and Crowding-Out

Rural bank branches are divided into two groups based on their distance from their respective regional headquarters. Panel A tests whether branches close to headquarters are different from branches located far away from their headquarters in terms of their lending characteristics. The first row shows mean branch-level total outstanding loan in thousands of Rupee. The next two rows show mean branch-level share of total outstanding loan that went to agricultural and manufacturing sector respectively. Standard errors are in parenthesis. The numbers in parenthesis for t-test represent the t-values. Panel B presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta_1 \text{Election}_{st} + \beta_2 \text{Election}_{st} * \text{Far}_i + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes bank branch, *s* indexes state and *t* denotes time. The dependent variable is the amount of credit in log. Column 1 uses agricultural credit, column 2 uses manufacturing credit while column 3 uses total credit. Election_{st} is an indicator variable that takes value of 1 in an election year and the year before an election. γ_{rt} is region-year fixed effects. Far_i is a dummy that takes the value of 1 for branches whose distance from their respective regional headquarters is greater than the median distance between a branch and its regional headquarter. X_{st} controls for time-varying state-specific characteristics—the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

Panel A: Branch Lending Characteristics

	Close	Far	t-test
Total Loan Outstanding ('000)	14,575	13,971	604
	[396.4]	[269.1]	[1.26]
Agriculture Share	0.427	0.404	0.02
	[0.0046]	[0.0047]	[3.479]***
Manufacturing Share	0.365	0.372	-0.007
	[0.0048]	[0.0040]	[-1.114]
N	4,977	4,902	

Panel B: Election Cycles

	Agriculture	Manufacturing	Total
	(1)	(2)	(3)
Election	21.77***	-2.85**	10.12**
	[6.12]	[1.10]	[4.77]
Election x Far	-9.81	-3.31**	-8.40**
	[7.13]	[1.66]	[3.89]
Branch Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	9,087	9,411	9,879
R-squared	0.76	0.78	0.81

Table 7: Credit Cycle and Loan Performance

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta_1 \text{Election}_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes bank branch, *s* indexes state and *t* denotes time. The dependent variable is the share of total credit late in payment. A loan is considered late if it is more than ninety days past due. Election_{st} is an indicator variable that takes value of 1 in an election year and the year before an election. γ_{rt} is region-year fixed effects. X_{st} controls for time-varying state-specific characteristics—the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Bad Loan	
	Agriculture	Manufacturing
	(1)	(2)
Election	1.28**	-0.29*
	[0.51]	[0.17]
Branch Fixed Effects	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year
Observations	15,380	22,523
R-squared	0.58	0.56

Table 8: Firm Leverage

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta \text{Election}_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. The dependent variable is firm leverage (debt scaled by the beginning of year book value of total assets) in log. Election_{st} is an indicator variable that takes the value of 1 during the election year and the year before. μ_{kt} controls for two digit industry-year fixed effects. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Firm Leverage	
	(1)	(2)
Election	-2.01**	0.56
	[0.75]	[1.33]
Election x		-5.81**
Share of workforce engaged in agriculture		[2.70]
Firm Fixed Effects	Yes	Yes
Industry Year Fixed Effects	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year
Observations	97,246	96,549
R-squared	0.71	0.71

Table 9: Cash Holdings and Investments

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta \text{Election}_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. The dependent variable in column 1 is the cash holdings scaled by the lagged book value of total assets whereas total firm investment scaled by the lagged book value of total assets is the dependent variable in columns 2 and 3. The dependent variable is in log scale in columns 1 and 2. Since investment is lumpy, column 3 uses the level of scaled investment instead of log to avoid dropping observations when investment equals 0. Average scaled firm investment during the off-election years was 7.6%. Election_{st} is an indicator variable that takes the value of 1 during the election year and the year before. μ_{kt} controls for two digit industry-year fixed effects. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Cash	Investment	
	(1)	(2)	(3)
Election	-2.04**	-3.55**	-0.29***
	[0.83]	[1.52]	[0.12]
Firm Fixed Effects	Yes	Yes	Yes
Industry Year Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year	Region-Year
Observations	130,119	107,741	128,954
R-squared	0.70	0.72	0.72

Table 10: Effect on Employment and Wages

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta Election_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. Dependent variables are in log. Employment numbers are scaled by beginning of year book value of total assets. Wages are calculated from total compensation and number of man-days worked. Information on temporary employees is only available for a subset of firms. Information on permanent employees is backed out from data on all employees and temporary employees. μ_{kt} controls for two digit industry-year fixed effects. $Election_{st}$ is an indicator variable that takes the value of 1 during the election year and the year before. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Employment			Wages		
	Temporary Employee	Permanent Employee	Total Employee	Temporary Employee	Permanent Employee	Total Employee
	(1)	(2)	(3)	(4)	(5)	(6)
Election	-3.26***	0.63	-1.21***	0.32	0.11	0.37
	[0.84]	[0.68]	[0.36]	[0.28]	[0.31]	[0.29]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year
Observations	47,734	40,720	128,865	46,709	39,596	126,005
R-squared	0.73	0.72	0.72	0.73	0.73	0.73

Table 11: Firm Production and Utilization

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta_{-j} Election_{st}^{-j} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. $Election_{st}^{-j}$ equals 1 if the next scheduled election is in *j* years for state *s* at time *t*. Dependent variables are in log. Production is scaled by the lagged book value of total assets in column 1. Production is measured as gross value added. In column 2, production is scaled by capital stock whereas in column 3, production is scaled by total labor compensation. In a Cobb-Douglas production function framework, the two ratios can be interpreted as the marginal revenue product of capital and labor, respectively. μ_{kt} controls for two digit industry-year fixed effects. In column 4, I replace capital stock with energy consumption to proxy for capital services use. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Production	Y/K	Y/L	$Y/K_{services}$
	(1)	(2)	(3)	(4)
4 Years to Election	-0.21	-0.35	-0.23	0.19
	[1.15]	[1.15]	[0.87]	[1.03]
3 Years to Election	1.45	0.11	0.48	-0.60
	[1.05]	[1.23]	[0.77]	[1.14]
2 Years to Election	2.97***	2.97***	1.86**	0.96
	[0.99]	[1.06]	[0.80]	[1.05]
1 Year to Election	1.11*	1.53	1.17	-0.07
	[0.60]	[0.90]	[0.76]	[1.01]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Time FE	Region-Year	Region-Year	Region-Year	Region-Year
Observations	98,413	98,933	99,101	99,236
R-squared	0.68	0.81	0.72	0.84

Table 12: Sales and Product Prices

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta_{-j} Election_{st}^{-j} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. $Election_{st}^{-j}$ equals 1 if the next scheduled election is in *j* years for state *s* at time *t*. Dependent variables are in log. The dependent variable in column 1 is product price. μ_{kt} controls for five-digit product-year fixed effects in this regression. The dependent variable in column 2 is sales scaled by lagged book value of total assets. μ_{kt} controls for industry-year fixed effects in column 2. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Price	Sales
	(1)	(2)
4 Years to Election	-4.30***	0.19
	[1.36]	[1.03]
3 Years to Election	-3.01**	0.90
	[1.19]	[1.11]
2 Years to Election	-2.74	0.82
	[2.18]	[1.28]
1 Years to Election	-4.27**	0.37
	[1.90]	[1.22]
Firm FE	Yes	Yes
Industry Year FE	Product-year	Yes
Time FE	Region-Year	Region-Year
Observations	225,189	113,665
R-squared	0.35	0.69

Table 13: Firm Heterogeneity

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta_1 \text{Election}_{st} + \beta_2 \text{Election}_{st} * I_{it} + \beta_3 I_{it} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, *s* indexes state and *t* denotes time. The dependent variable is log of total debt scaled by lagged book value of asset. Election_{st} is an indicator variable that takes the value of 1 in an election year and the year before an election. I_{it} is a dummy that takes the value of 1 if firm *i* is located in a rural area (Rural—column 1), or is not publicly listed (Private—column 2. μ_{kt} controls for two digit industry-year fixed effects. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

	Firm Leverage	
	(1)	(2)
Election X Rural	-3.14***	
	[1.05]	
Election X Urban	-0.73	
	[1.11]	
Election X Private		-2.25**
		[1.02]
Election X Public		-0.44
		[1.04]
Firm FE	Yes	Yes
Industry Year FE	Yes	Yes
Time FE	Region-Year	Region-Year
Observations	97,246	97,246
R-squared	0.71	0.71

Table 14: Capacity Utilization across Firms

This table presents results for the following regression:

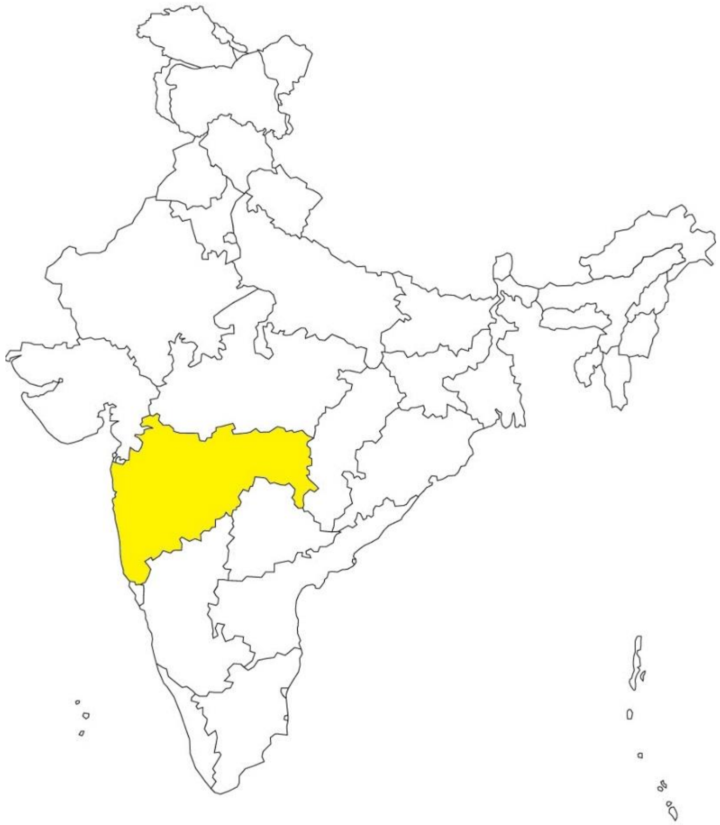
$$y_{ijst} = \alpha_i + \gamma_{rt} + \mu_{kt} + \beta_j \text{Election}_{st} \text{ X } Tertile_j + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes firm, j indexes tertile group, *s* indexes state and *t* denotes time. The dependent variable is log of capacity utilization, defined as gross value added (gva) scaled by the average of the beginning and the ending value of capital stock. Election_{st} is an indicator variable that takes value of 1 in an election year and the year *after* an election. The effect of lending squeeze on production is observed during these two years. $Tertile_j$ is an indicator variable that equals 1 if the firm belongs to the j_{th} tertile group. The coefficient β_j represents the effect of election on capacity utilization rates for firms belonging to tertile *j*. Sorting into tertile groups is done based on sales, book value of fixed assets, or number of employees. All firms are pooled together in column 1. Columns 2, 3 and 4 exclude firms from tertile 1 in order to examine if the result in column 1 is exclusively driven by small firms. Columns 4, 5 and 6 estimate separate coefficients for firms in the three tertile groups. μ_{kt} controls for two digit industry-year fixed effects. γ_{rt} is region-year fixed effects. X_{st} is the state GDP growth rate. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The point estimates and standard errors are multiplied by 100.

		Restricted Sample			Sorted by		
	Pooled	Sales	Size	Employment	Sales	Size	Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election	-1.85***	-1.51	-1.58*	-2.14**			
	[0.57]	[1.04]	[0.81]	[0.83]			
Election X Tertile1					-2.09	-2.06	-1.45
					[1.40]	[1.38]	[1.37]
Election X Tertile2					0.11	-1.55*	-2.02
					[0.14]	[0.77]	[1.17]
Election X Tertile3					-3.64***	-2.11	-2.16
					[1.25]	[1.27]	[1.34]
GVA ratio - tert1:tert2:tert3					1:5.8:82.1	1:4.9:55.6	1:3.9:25.2
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year	Region-Year
Observations	98,933	65,795	65,799	65,863	98,933	98,933	98,780
R-squared	0.82	0.72	0.72	0.77	0.82	0.82	0.81

Figure 1: State Elections in India

Figure on the left shows a map of India with the state boundaries. The state elections are staggered over time, with each state following its own five-year cycle. Table 2 shows the distribution of state elections during the 1999-2008 period. The state of Maharashtra is shaded. Figure on the right illustrates election in Maharashtra. Being a relatively large state, it has 288 election constituencies. Voters directly elect a representative from each election constituency. The party or coalition with a simple majority of representatives is invited to form the government at the state level.



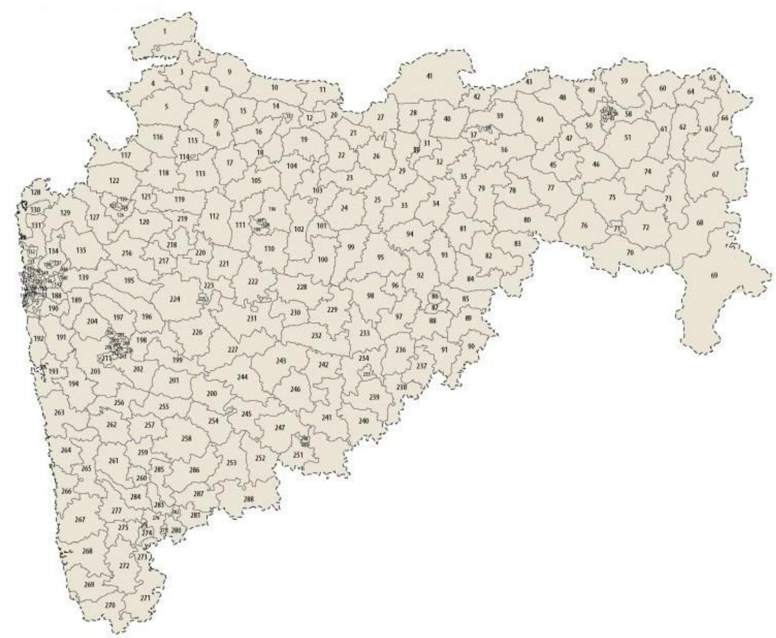


Figure 2: Election Cycle in Bank Lending

Figure uses data on total bank lending by industry in each district of 20 large states in India. Each district-year observation is assigned to one of the five bins – two years before an election, one year before an election, election year, one year post-election and two years post-election. For each bin, the share of total credit extended to the agricultural sector and manufacturing sector is shown.

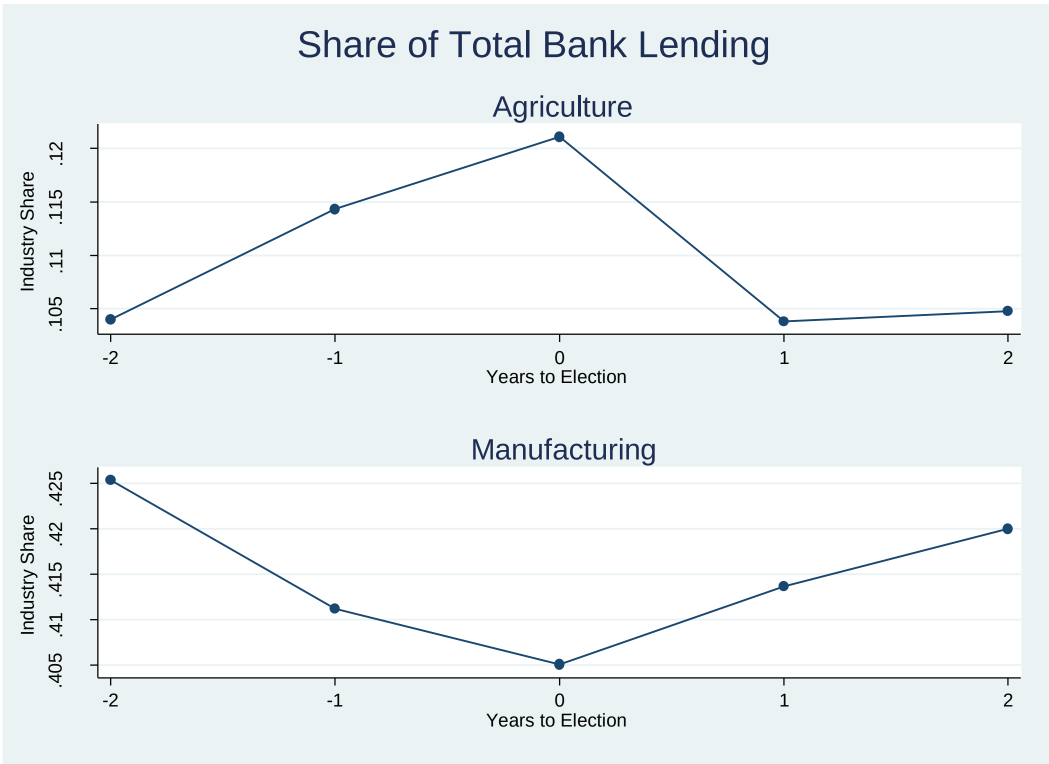


Figure 3: Loan Performance

This figure plots coefficients from the regression in Table 7, where the election dummy is replaced by a set of indicator variables denoting number of years to next election. The coefficients denote the share of agricultural or manufacturing loans late in payment by more than 90 days.

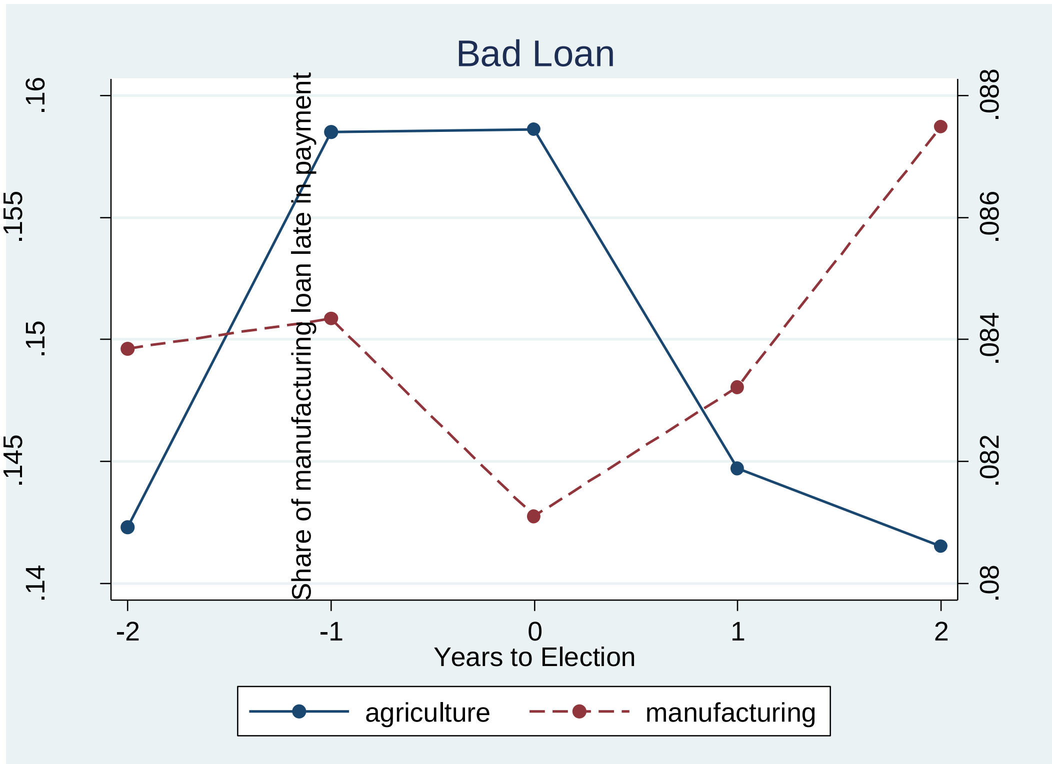
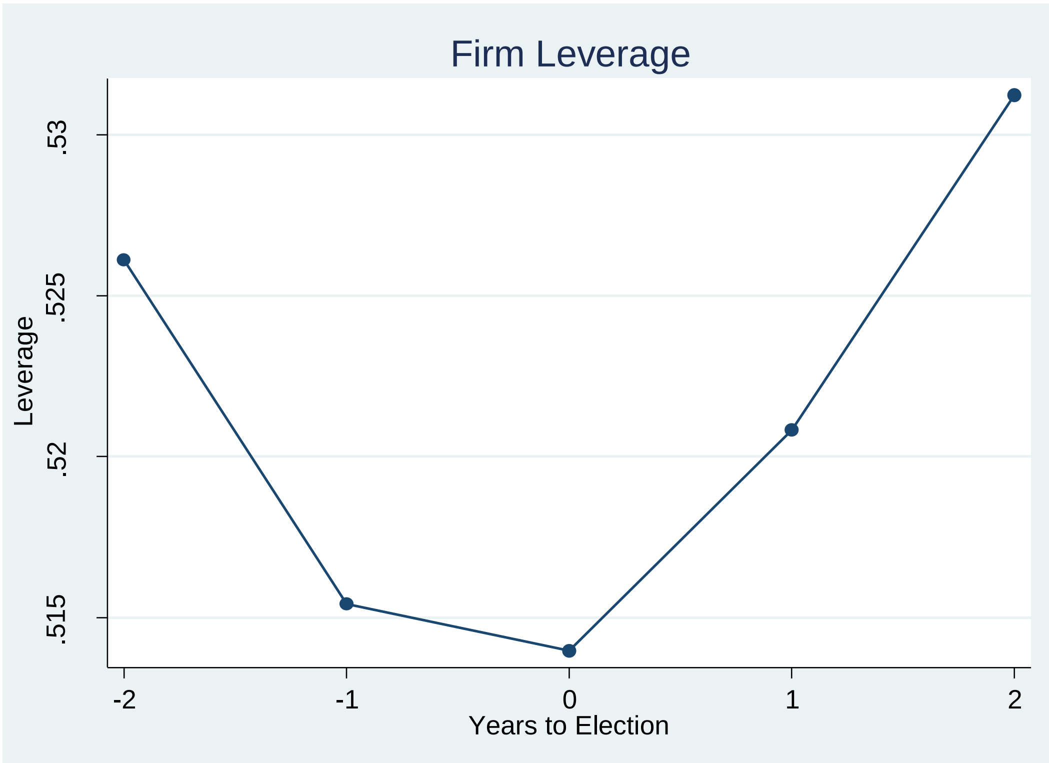


Figure 4: Election Cycle in Firm Leverage

This figure shows variation in firm leverage with time to election. Firm leverage is defined as total debt outstanding scaled by the book value of total assets. Each firm-year observation is assigned to one of the five bins – two years before an election, one year before an election, election year, one year post-election and two years post-election. For each bin, median firm leverage is shown.



Internet Appendix

Table A1: Bank Lending Cycle: Instrumental Variable Approach

This table presents results for the following regression:

$$y_{ist} = \alpha_i + \gamma_{rt} + \beta \text{Election}_{st} + \delta X_{st} + \varepsilon_{ist}$$

where *i* indexes bank branch, *s* indexes state and *t* denotes time. The dependent variable is the amount of credit in log extended to either the agricultural sector or manufacturing sector. Election_{st} is an indicator variable that takes the value of 1 during an election year and the year before. The coefficients reported in the table represent the percentage change in lending when Election_{st} equals 1. γ_{rt} is region-year fixed effects. X_{st} controls for time-varying state specific —the amount of rainfall for agriculture, and the state GDP growth rate for manufacturing. Panel A reports results from ordinary least squares regression. In panel B, the election indicator Election_{st} is replaced by E_{st}^{IV}, which takes a value of 1 if four or five years have passed since the last election. Panel C reports results from a two-stage least-squares regression. Standard errors are clustered by state. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. R-squares appear below standard errors.

	Agriculture	Manufacturing
	(1)	(2)
Panel A: OLS	0.092***	-0.026**
	[0.027]	[0.010]
	0.74	0.92
Panel B: Reduced Form	0.084***	-0.023**
	[0.026]	[0.010]
	0.73	0.91
Panel C: IV	0.085***	-0.024**
	[0.026]	[0.010]
	0.73	0.91
Branch Fixed Effects	Yes	Yes
Time Fixed Effects	Region-Year	Region-Year
Observations	15680	22853