Anatomy of Depositor Disciplining Mechanism: Selection, Voice and Exit*

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Abstract

Using data on Indian cooperative banks, we find that banks with big depositors are less engaged in fraudulent lending, and have higher asset quality and profitability than banks with small depositors. Moreover, banks with big depositors are ex-ante safer because they are more vulnerable to deposit outflows and this vulnerability disciplines banks' behavior. Our empirical results support the argument that depositors have incentives to monitor banks even in the presence of deposit insurance, and big depositors have more incentives to monitor banks than small depositors.

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1 Introduction

Depositors monitor banks to reduce their losses from bank runs. They pay a cost to collect information on banks' investment decisions, and decide when to withdraw their deposits after receiving negative information (Calomiris and Kahn (1991)). Banks are thus vulnerable to runs, especially when demand deposit is the primary source of bank funding and banks' assets have much longer maturity than their liabilities (Diamond and Dybvig (1983)). The vulnerability of banks serves as a disciplining device, reduces bank failure, and leads to more efficient allocations (Diamond and Rajan (2001)). Hence, the efficiency of the banking sector crucially depends on depositors' monitoring incentives. The literature has argued that, with deposit insurance, depositors no longer have incentives to monitor banks, because they don't incur losses from bank failure. In this paper, however, we provide empirical evidence that depositors still monitor banks in the presence of deposit insurance, and argue that the results are driven by depositors' non-pecuniary benefits from banking relationship and incomplete deposit insurance.[1]

We exploit a unique institutional setting in Indian cooperative banks, where deposits are insured but depositors still monitor banks for two reasons: (1) Besides monetary return from their deposits, depositors also receive non-pecuniary benefits from relationship banking and they lose these benefits when bank fails; (2) Deposit insurance is incomplete, i.e. it only compensates depositors with a lag. Depositors care about the time value of money, and more importantly, they may suffer from liquidity shocks due to the payout delay. In either case, depositors incur losses from bank failure, and thus have incentives to monitor banks by voicing their concerns and imposing the threat of run.

Our empirical strategy relies on the assumption that big depositors have more incentives to monitor banks than small depositors. This is because they enjoy more non-pecuniary benefits and are more vulnerable to liquidity shocks in case of payout delay. Under this assumption, banks with big depositors (concentrated banks) are more closely monitored than banks with small depositors (non-concentrated banks), and do less politically-motivated

[1] The non-pecuniary benefits we have in mind include benefits such as the ease in getting loan facilities for themselves, friends and family, shorter waiting time etc. Complete insurance market ensures that the depositors can withdraw their insured amount anytime they want even after bank failure. If complete insurance markets exist, depositors should be able to drive to the deposit insurance agency and demand their deposit if they are declined by their bank, or buy a costless security which allows her to do the same.

fraudulent lending. We measure depositor size by the average deposits per depositor (call it deposit concentration hereafter), and capture fraudulent lending by the change in bank lending in periods of simultaneous state and federal elections.

We begin by documenting that concentrated banks do less fraudulent lending than non-concentrated banks. When deposit concentration increases from the first quartile to the third quartile, banks reduce fraudulent lending by 2.5%. Then we look at bank lending by sectors, and find that concentrated banks reduce fraudulent lending to both priority sectors and non-priority sectors, and the reduction in fraudulent lending to priority sector is driven by small-scale industries. Moreover, our results are robust to various fixed effects and time-varying bank characteristics. These results support our hypothesis that depositors still monitor banks even with deposit insurance, and big depositors have more incentives to monitor banks than small depositors.

Interestingly, bank fixed effects could explain a significant portion of the reduction in fraudulent lending. This is evidence for big depositors ex-ante selecting into better banks than small depositors. Consistent with the selection mechanism from consumer theory (Hirschman (1970) and Le Grand (2009)), depositors select banks ex ante based on their noisy signals.

We then document that depositor monitoring improves banks' asset quality and profitability on average. Following electoral shocks, banks with deposit concentration at the third quartile have a 0.8% lower non-performing loan (NPL) ratio and a 0.6% higher return on advances than banks with deposit concentration at the first quartile. And the results are not driven by differential net interest margin or cost of funds in the two groups of banks.

However, depositor is not always successful in disciplining banks. When depositors fail to do so, they exit banks to avoid further losses. Following a 1% increase in NPL ratio, banks in the third quartile of deposit concentration suffer from 10% more outflow in deposits relative to banks in the first quartile of deposit concentration. This suggests that big depositors do exit banks when banks ignore their voices, while small depositors are insensitive to banks' misbehavior.

The above empirical findings complete the whole picture of the depositor monitoring mechanism, which comprises of three stages: selection, voice and exit. At the selection stage, depositors select banks based on their ex-ante information. Then at the voice stage, depositors collect information on banks' behavior. If they detect misbehavior, they first voice their concerns (combined with the threat of run) to banks rather than exit banks because developing a new banking relationship is costly. At this stage, depositors are willing to pay a cost to collect information and voice their concerns to banks, because they lose non-pecuniary benefits and are exposed to liquidity shocks when banks fail. Finally, if banks ignore depositors' voices, depositors will exit banks to avoid further losses.

1.1 Related Literature

Our paper contributes to both the empirical and theoretical literature on depositor monitoring. Calomiris and Kahn (1991) show that demand deposits provide incentive-compatible intermediation when the banker has comparative advantage in allocating investment funds but may act against the interests of uninformed depositors. Uninformed depositors actively collect information on bank fundamentals to decide on the best time to withdraw from banks. However, their depositor monitoring story breaks down in the presence of deposit insurance, because they make two assumptions: (1) Depositors lose money in case of bank failure; (2) Depositors only care about monetary return of their deposits. In this paper, we exploit the unique institutional features in Indian cooperative banks, and show that when the above two assumptions no longer hold, depositors still have incentives to monitor banks.

On the empirical side, Steiner and Barajas (2000) use data from Columbia to show that depositors prefer banks with strong fundamentals. More recently, Homanen (2018) study the negative relationship between deposit growth and scandals. Calomiris and Jaremski (2019) use data on the early 20th century US banks, and show that deposit insurance removes market discipline. Our empirical tests add to the empirical literature by documenting the positive effects of depositor monitoring in the presence of deposit insurance. Our results explain the facts presented in Iyer and Puri (2012) that bank-depositor relationship reduces bank vulnerability, and in Iyer, Puri and Ryan (2016) that bank fragility depends on the composition of its deposit base. Additionally, our results are related to Diamond and Rajan (2001). We show that depositor monitoring makes bank fragile and thus ex-ante safer.

The rest of the paper proceeds as follows. Section 2 presents a simple model that illustrates the selection, voice and exit mechanism. Section 3 discusses the institutional backgrounds. Section 4 describes the data. Section 5 discusses the empirical strategy. Section 6 presents the results and discusses the interpretations. Section 7 concludes.

2 The Depositor Monitoring Mechanism

In this section, we present a simple framework for thinking about the depositors' selection, voice and exit mechanism. The setup features asymmetric information between banks and depositors, and depositors monitoring banks by collecting information on bank fundamentals.

2.1 Setup

Time is discrete, and there are four periods $t = 0, 1, 2, 3$. At $t = 0$, depositors choose banks to deposit their money and decide whether to pay a cost to monitor the banks. The banks observe their depositors' types and their monitoring decision, and then invest in a project and decide whether to "work" or "shirk" on the project. At $t = 1$, depositors decide whether to run from banks. At $t = 2$, depositors and banks split the project payoffs. At $t = 3$, depositors are compensated by deposit insurance if they incur a loss at $t = 2$.

2.1.1 Agents

There are two risk-neutral depositors – a big depositor and a small depositor. The big depositor has initial wealth w_B and the small depositor has initial wealth w_S, where $0 < w_S < w_B$. Let c_t denote a depositor's net income at time t, then his preference is given by $c_1 + c_2 + \rho c_3, \rho \in (0, 1)$. ρ captures the payout delay by the deposit insurance. The big depositor derives private benefit b_B from an established banking relationship, i.e. if she does not run at $t = 1$, she receives b_B at $t = 2$. The small depositor derives private benefit b_S from an established banking relationship, i.e. if he does not run at $t = 1$, she receives b_S at $t = 2$. We assume that $0 < b_S < b_B$.

There are two risk-neutral banks – a good bank and a bad bank. The banks have access to the same type of investment project. The project has return R if it succeeds and 0 if it fails. The bank can work to increase the project's probability of success. In particular, if a bank shirks, the probability of success is p, while if he works, the probability of success is $p + \Delta_p$. The banks do not incur any additional cost from working/shirking. A bank can also liquidate the project at $t = 1$ with some deadweight loss. Specifically, if the bank liquidates the project, it can only get back γ fraction of its initial investment.

The two banks differ in their private benefit from investing. If the project fails, the good bank gets k_G private benefit from the project, and the bad bank gets k_B private benefit from the project. If the project succeeds, both banks get 0 private benefit from the project. This captures the conflict of interest between banks and depositors. And we think of k_B, k_G as capturing banks' political connections.

2.1.2 Monitoring

Both types of depositors can pay cost c at $t = 0$ to monitor the banks. If a depositor monitors the bank, he will be able to learn whether the bank works or shirks at $t = 1$ before he makes withdrawal decisions. If a depositor does not monitor, he will learn this information only at $t = 2$. Besides, if the two depositors deposit in the same bank and only one depositor monitors the bank, then the depositor who monitors will be served first when both depositors withdraw. Finally, a bank knows whether a depositor monitors or not before the bank makes a decision on working or shirking.

2.1.3 Contracts between Banks and Depositors

A bank writes debt contract with its depositors. We assume the contract specifies that, for a depositor who deposits w in the bank:

- The depositor has the right to either withdraw w or not withdraw at $t = 1$.
- If the bank repays all withdrawals by liquidating a fraction of the project, the remaining deposits are still invested in the project and generate return. If the bank does not liquidate enough projects to pay the full amount of withdrawals, then the bank fails and has to liquidate all the projects at $t = 1$ and distribute the liquidation value to depositors up to their initial deposits.

- If the bank does not fail at $t = 1$, then at $t = 2$ all depositors observe the project return (regardless of whether they monitor or not), the project's payoff is distributed to the remaining depositors up to their initial deposits.

2.1.4 Deposit Insurance

The government provides deposit insurance which only pays depositors at $t = 3$. It guarantees that at $t = 3$, a depositor with w of initial deposits and already receive x from the bank will get an additional $\max\{\min\{\bar{w}, w\} - x, 0\}$ from deposit insurance. We assume that $0 < w_S < w_B < \bar{w}$, so both small and big depositors get at least all their initial deposits back (ignoring the time value of money).

2.1.5 Timeline

At $t = 0$, a depositor first chooses which bank to deposit his money and decides whether to invest in the monitoring technology or not. If she invests, she pays c. After seeing each depositors' decision on monitoring, the banker chooses a project and invests all deposits she receives in that project. At $t = 1$, depositors who invest in the monitoring technology learns which project the bank has chosen, while others don't. Each depositor then decides on whether to withdraw his initial deposit or not, based on all available information. Those who withdraw receive money according to the contract. At $t = 2$, remaining depositors receive money from the bank according to the contract and the banker gets his private benefit. At $t = 3$, depositors get paid under deposit insurance.

2.2 Assumptions

1. $p \in (\gamma, 1), \Delta_p \in (\gamma, 1 - p)$.

2. $c \in ((1 - \rho) \Delta_p w_S, b_S)$.

3. $k_B > R - 1$.

4. $b_B < \gamma (1 - \rho) (w_B + w_S) + p\rho w_B$.

5. $\gamma < \frac{w_S}{w_B + w_S}$.

2.3 Equilibrium

As described above, banks and depositors play a sequential game and we solve for the Nash equilibria of the game. We have the following proposition

Proposition 2.1. *Under the above assumptions, there is a Nash equilibrium where the players use the following strategies:*

- *The big depositor deposits in the good bank and monitors. She runs if the good bank shirks and does not run if the good bank works.*
- *The small depositor deposits in the bad bank, does not monitor and does not run.*
- *The good bank works if and only if all depositors in the bank monitors.*
- *The bad bank works if and only if all depositors in the bank monitors.*

In this equilibrium, the big depositor chooses the good bank and monitors. The good bank works and the big depositor does not run. The small depositor chooses the bad bank and does not monitor. The bad bank shirks and the small depositor does not run. The good bank thus has higher "deposit concentration" (measured by per capita deposit) than the bad bank.

We leave the proof to Appendix A.

The intuition is as follows. The big depositor monitors the bank because his private benefit is large enough relative to the monitoring cost. If the small depositor also chooses the good bank, then he has to monitor the bank to prevent the bank from shirking (even if the good depositor also monitors). The small depositor does not choose the good bank for two reasons: first, since his private benefit is not large enough relative to the cost of monitoring; second, if he does not monitor and free-ride on the big depositor's monitoring, then the bank shirks and the big depositor has priority to withdraw when they both run from the bank. Hence, the small depositor chooses the bad bank instead. The small depositor does not monitor the bad bank, and the bad bank shirks.

In this equilibrium, big depositor select the bank that performs better ex post, and he voices his concerns to the bank by actively monitoring the bank's project choice. The big depositor has more incentive to monitor the bank than the small depositor precisely because he derives more private benefit from the banking relationship. And the threat of a run, as an exit mechanism, disciplines the good bank ex ante.

3 Institutional Background

An ideal setting to test our depositor monitoring mechanism is one where: (1) banks are predominantly deposit-dependent institutions; (2) banks are small so that depositors have bargaining power over banks; (3) depositors receive large private benefits from the banking relationship and thus they have incentives to monitor banks; (4) all deposits are insured; (5) deposit insurance is incomplete; (6) we can identify banks' fraudulent lending. Cooperative banks in India and the Indian electoral cycle provide an ideal laboratory to test the mechanism.

3.1 Cooperative banking

From humble beginnings coinciding with the enactment of the *Cooperative Societies Act* 1912, the cooperative sector in India has come a long way, being organised on the basis of 'one member, one vote' with the focus of dispensation of credit at the micro level, especially the small and marginal farmers and other under-served segments of the population. According to the Organization for Economic Cooperation and Development (2012), in 2009, there were over 1,000 cooperative banks in Germany with assets totalling USD \$970 billion and close to 500 in Italy with assets of USD \$700 billion. The numbers for the United States were much smaller, numbering 60 with an asset base of US \$15 billion. As compared to this, India had a total of 1,700 cooperative banks in the same year, with a total book value of asset aggregating USD \$40 billion.

With over 150,000 outlets, the cooperative system has a total membership in excess of 150 million. In terms of asset share, the share of cooperative banks in total banking asset is around 6-8%, with commercial banks accounting for the remaining. Notwithstanding the growing footprints of commercial banks, the cooperatives dominate in terms of their reach to the rural hinterland, averaging one ground level credit cooperative for every five villages, making it one of the extensive financial systems globally – in terms of both the number of clients served and the members involved. At the end of 2013, a total of 2,724 cooperatives were operating in urban and rural areas of the country, with total asset close to INR 8,000 billion ($\approx$ USD \$120 billion), equivalent to 7% of India's 2013 GDP.

Cooperative banks can be classified into two categories: urban and rural. As the names suggest, the former focuses on credit-delivery in urban areas, whereas the latter caters to rural areas. As of end-March 2013, the total assets of urban cooperative banks (UCBs) aggregated INR 3,373 billion ($\approx$ USD \$50 billion)[2]. Within the UCBs, there is a distinction between scheduled and non-scheduled banks. Figure 1 gives a schematic representation of the banking structure of cooperative banks. The scheduled UCBs include banks that have paid-up capital and reserves not less than INR 500,000 ($\approx$ US \$7500) and are included in the second schedule of the Reserve Bank of India (RBI) Act, 1934 which provides them access to the liquidity window of the Indian central bank.[3] These banks are subject to regulatory and prudential norms as prescribed by the Indian central bank, although they are less stringent as compared to commercial banks. As compared to this, the non-scheduled UCBs are subject to light-touch regulation (Reserve Bank of India Report (2012)). The operations of both scheduled and non-scheduled UCBs are either limited to one state or span multiple states. Most non-scheduled UCBs are primarily single-state so that their bank-level operations coincide with the branch. As compared to this, several large scheduled UCBs have a multi-state presence. For example, Shamrao Vittal Cooperative Bank headquartered in Mumbai of Maharashtra state had a total of over 250 branches in 2013 across eight states. In contrast, Eenadu Cooperative Bank headquartered in Hyderabad in the state of Telangana has a total of six branches, all in the same state.

In terms of regulatory stipulations, UCBs are required to extend a minimum percentage of their total loans to designated (priority) sectors. This minimum percentage is fixed at 40% and a quarter of this amount has to be provided to weaker sections, such as small and marginal farmers, distressed farmers who are indebted to non-institutional lenders, self-help groups, and women. Unlike commercial banks which have a minimum sub-target for agriculture, for cooperative banks, there is no sub-target for agriculture but instead, there

[2]The financial year for banks run from the first day of April of a given year to the last day of March of the subsequent year. Accordingly, the year 2006 coincides with the period 2006 (April) – 2007 (March) and so on for the other years.

[3]The Reserve Bank of India is the central bank of the country.

are targets for lending to micro and small enterprises (MSEs). In particular, 40% of total advances to micro and small enterprises sector should go to micro (manufacturing) enterprises and micro (service) enterprises.[4] Within this overall ceiling, 20% of the advances have to be provided to micro-enterprises. By way of comparison, commercial banks in the country have to provide 7.5% of their total loans to micro-enterprises. Available information reveals that the share of loans to designated sectors has increased from 43% in 2004 to nearly 60% in 2013; the share of loans to MSEs has hovered around 42%, whereas loans to weaker sections have been range-bound at about 25% during this period.

Two features of the sector are of interest. The first is the high level of regional concentration. Over 80% of all UCBs are located in the Western and the Southern regions of the country. At a further level of disaggregation, the share of the top three states in respect of both deposit and credit is over 80%. The second is the dual control of these entities wherein their banking-related activities are regulated by the Indian central bank, whereas the registration and management-related activities are under the purview of respective state governments. To address this challenge, a Memoranda of Understanding (MoU) has been signed with the respective state governments under the aegis of the *Banking Regulation Act*, 1949 (as applicable to cooperative societies).

3.2 Elections

The Indian constitution provides for a federal system much like the United States. Federal parliamentary elections are typically held every five years or alternatively when the current government loses majority control.[5] Once called, the election is scheduled and conducted by a constitutionally empowered Election Commission of India (ECI). The electoral process follows the first-past-the-post system: after the elections, the candidate with the largest percentage of votes, irrespective of the magnitude of the fraction, is declared the winner. Votes are cast by secret ballot and anyone over the age of 18 is allowed to vote. During the period 2002-2014, there have been three federal elections – in 2004, 2009 and 2014.

[4]Micro (manufacturing) enterprises are those with investment in plant and machinery above INR 1 million and up to INR 2.5 million and micro (service) enterprises are the ones with investment in equipment above INR 0.4 million and up to INR 1 million.

[5]The federal elections appoint elected representatives to the lower house of the Parliament referred to as *Lok Sabha*.

State elections are normally held every five years, wherein members are also elected directly by the people of the constituencies.[6] From 2004 till 2013, there have been over 60 state elections. State elections were formally de-linked from *Lok Sabha* elections in 1969 when several states conducted separate elections. In this study, we use the simultaneous occurrence of federal and state elections (dual elections, hereafter) as electoral shocks. We do this for two reasons. One these shocks are bigger shocks as a greater amount of legislative power is at stake giving myopic voters greater bargaining power in extracting political benefits. Secondly, the governance structure of cooperative banks as described in section 3.1 is marked by dual control of the state and the federal government.

3.3 Political influence and Cooperative Banks

The cooperative banking sector is a cesspool of politics. In 1966, when the law governing commercial banks in the country was also made applicable to these banks, there were about 1,100 of them with deposits and advances of INR 1.7 billion and INR 1.5 billion, respectively. The next several decades witnessed a phenomenal growth with their deposits rising to INR 1.1 trillion and lending to over INR 700 billion. With business growth, the politicization of the sector also increased manifold. These banks have become the conduits for distributing political patronage.

Several academic and policy documents have examined various facets of the functioning of these banks and highlighted the high degree of political interference. For example, Gould (2010) had highlighted the serious embezzlement of funds from a local cooperative bank by a leading politician in the state of Uttar Pradesh in the early 1950s. In 2002, the Indian government enunciated a National Cooperative Policy to facilitate the all-round development of the cooperative sector. A Ministerial Task Force was set up to formulate an action plan for its implementation. The Task Force recommended a move to depoliticise the cooperatives so that members elected to the legislative assemblies or the *Lok Sabha* should not be elected as senior functionaries of these banks. Thereafter, the High Powered Committee set up by the Government of India in 2009 to identify the challenges confronting the sector and

[6] The state elections appoint elected representatives to the lower house of the State Legislative Assembly referred to as *Vidhan Sabha*.

suggest appropriate remedial legislative changes also highlighted the high level of political interference in the sector (Planning Commission Report (2009*b*)).[7]

Around the same time, the Committee on Financial Sector Reforms chaired by Raghuram Rajan also lamented the high level of political interference in the sector (Planning Commission Report (2009*a*)).[8] Anecdotal evidence shows that minimizing political interference actually helped turn a loss-making cooperative bank into a profitable institution.[9] A report prepared in 2015 by *Sampark*, a Bangalore-based non-governmental organization (NGO) engaged in children education and women's empowerment for the United Nations Development Programme (UNDP) documents several instances of political interference in these banks which ultimately compromised on their viability and sustainability.

An indirect testimony of the political interference in these banks can be gleaned from the deposit insurance paid. Since its inception, the Deposit Insurance Corporation of India has paid around INR 64 billion ($\approx$ US $1 billion) in claims to deposits after bank failures. Over 50% of this amount – around INR 33 billion – has been paid out during 2009-2013 to over 150 cooperative banks, although the contribution to the deposit insurance fund by these banks averaged less than 9% during the period (Deposit Insurance Corporation Annual Report, various years).

[7]In the words of the Committee: *"Although cooperative democracy is based on common economic interest and as such is entirely different from political democracy, over time cooperatives have been increasingly politicized. Cooperative institutions in the country with their vast outreach have become powerful instruments of political mobilization. Instances of a political party in power assuming control over large sized cooperatives through methods such as appointing an active member of the party to the position of Chairman, nominating persons of its choice on the Board, issuing directions to them and the Official nominees to vote for a particular candidate as Chairman has become common. Further, when elections are held, they are fought on party lines with panels of political parties keenly contesting to gain control of the organization. This has led to factions in the board, conflicts in governance and management and lack of consensus in decision making. Also, factors such as personal/political interests of board members and use of the cooperative for political patronage have weakened the cooperative sector and affected their ability to function as competitive and professionally managed business entities"*.

[8]The committee observed: "Cooperative banks, both urban and rural, are the face of banking that most Indians encounter. Unfortunately, primarily because of excessive political interference, poor governance and a willingness of governments to recapitalize and refinance even poor performers, this sector has underperformed seriously" (pp.8).

[9]The Indian Express (June 22, 2014) reported that Maharashtra State Cooperative Bank (MSCB) which was running at a loss for quite some time turned around to post an INR 6 billion profit in 2013-14 from an accumulated loss of INR 18 billion in 2010-11. This happened when the state government intervened in its functioning and replaced the existing board of directors with more professional management. The state's Minister for Cooperatives and Parliamentary Affairs observed "Political interference in running the MSCB or district cooperative banks has caused immense damage to these institutions. My ministry had to take stern measures to set the system right and restore the faith of depositors in cooperative banks."

3.4 Deposit Insurance

Similar to the Federal Deposit Insurance Corporation (FDIC) in the US, bank deposits in India are insured by the Deposit Insurance and Credit Guarantee Corporation (DICGC). DICGC was established in 1978 under the DICGC Act of 1961. DICGC insures all bank deposits, up to the limit of INR 100,000 ($\approx$ USD 1,500).[10] This insured amount includes both the principal and the interest amount. Different accounts of the same individual within the same bank are treated as one for the computation of the deposit insurance limit. However, accounts in different banks of the same individual are considered separate. The insurance premium is paid by the banks. DICGC has the power to cancel the registration of the bank if it fails to pay the insurance premium for three consecutive half-quarters. However, unlike FDIC, DICGC does not have any bank supervisory power.

A distinctive feature of deposit insurance in India is that it suffers from a payout delay. This creates a market incompleteness in deposit insurance markets. Figure 2 shows the kernel density of payout delays by DICGC for cooperative banks that failed between 2006 and 2013. Conditional on payout we observe a mean value of 4.2 years. This results in losses due to the time value of money.[11] Additionally the long payout time exposes these borrowers to liquidity shocks.

4 Data

We collect novel confidential data on Indian cooperative banks from the Reserve Bank of India. The bank-level data includes information collected as part of the prudential supervisory reporting system under the off-site surveillance (OSS) mechanism submitted to the central bank. In emerging markets such as India, comprehensive data on cooperative banks was not collected earlier. However, over the past decade and a half, there has been a spate of several high profile bank failures in the sector.[12] Following the recommendations of a Joint Parlia-

[10] The deposit insurance limit is equal to the gross domestic product per capita in 2016 in India.

[11] One can understand the time value of money losses by looking at the opportunity cost. The risk-free rate in India was around 8% on average for the period between 2006 and 2013. For small constrained business owners the borrowing rate is usually high. For example, 20% is the rate at which the government requires buyers to compensate Medium, Small and Micro Enterprises (MSME) for delayed payments under the Micro, Small and Medium Enterprises Development Act, 2006.

[12] One major reason for cooperative bank failure has been the dual control of these entities. To be more specific, the Indian central bank is entrusted with the responsibility of regulation and supervision of the banking-related activities

mentary Committee, the central bank has begun collecting information on various facets of operations of these banks.

As a first step, scheduled urban cooperative banks had to prepare annual returns and submit these to the central bank beginning 2003.[13] It was not until a year later that these returns stabilized. A key feature of these annual returns is the preparation and reporting of balance sheet and profit and loss statements in a prescribed format, including important prudential ratios. Besides being subject to post-facto verification during on-site inspections, these returns also formed the basis for supervisory attention and dialogue with bank management. Effective 2005, the submission of returns by these banks were extended to non-scheduled urban cooperative banks with a deposit base of INR 1,000 million ($\approx$ USD 22.7 million).

At the end of March 2013, the sector comprised of 1,606 banks, which includes 51 scheduled banks, with the remaining being non-scheduled. While the number of scheduled banks has remained broadly unaltered over time, the number of non-scheduled banks has gradually declined, reflecting to an extent, the impact of mergers, amalgamations and liquidations in the sector.[14] Using this database, we hand-collect information on these banks beginning 2004, the first year for which consistent data on most of the relevant variables is available. Table 1 provides a comparison of our data sample with the whole sector of UCBs. The sample size is comprehensive in terms of scheduled UCBs, and much less so for non-scheduled UCBs during the initial years, but improves over time as more and more such banks began reporting information. In order to avoid any sample issues, we begin our analysis in 2006. We obtain data on nearly 1,600 banks. Unlike earlier studies which are based on small samples or confined to one or a couple of states, our data covers an extensive sample of banks across all major states and as a result, provide much more conclusive evidence

of primary co-operative banks under the Banking Regulation Act, 1949 (As Applicable to Co-operative Societies, AACS). However, other relevant aspects such as incorporation, registration, administration, management and winding-up of these entities are supervised and regulated by the respective State Governments through Registrars of Co-operative Societies (RCS) under the Co-operative Societies Acts of the respective States. UCBs with a multi-state presence are registered under the Multi-State Co-operative Societies Act, 2002 and are regulated and supervised jointly by the Central Government through Central Registrar of Co-operative Societies and the Reserve Bank.

[13]Scheduled banks are those which are included in the Second Schedule of the RBI Act, 1934, which entails them to (a) become eligible for liquidity facilities from the central bank and (b) acquire automatic membership of clearing houses.

[14]The financial year for banks extends from the first day of April of a given year to the last day of March of the following year.

regarding the behaviour of these banks. Figure 3a and 3b provide a detailed description of cooperative bank lending and its spatial distribution from our sample of UCBs between 2006 and 2013. On average, these banks account for 80% of the total assets of UCBs during the period.

The information collected includes, in addition to the district the bank is located, the book value of asset and equity as well as income-expenditure details, such as interest earned on loans, interest expenses on deposits and borrowings and the share of non-performing loans in total loans. In addition, the data provide details of total loans extended during the year by each bank, including at a dis-aggregated level such as those to priority (PSL) and non-priority (Non-PSL) sectors, medium and small enterprises (MSE) and medium and large industries (MLE). Within the former category, there is information on the amount of credit extended to agriculture, small scale industries, small businesses and other priority sectors.[15] Using these numbers, we compute the variables of interest, such as log total (real) credit including its sub-components as well as other related indicators such as size, equity-to-asset, net interest margin, return on credit and cost of funds. Table 2 reports summary statistics of key variables used in our analysis. The definition of variables used in the study are reported in appendix B.

5 Empirical Strategy

The empirical strategy consists of two steps. First, we show that banks increase lending during election periods, and we argue that the increased lending is a reasonable measure of politically-motivated fraudulent lending. Next, we use a within-district-year estimator to show that big depositors monitor banks more closely than small depositors and thus reduce

[15] This includes loans not exceeding INR 50,000 (≈ USD 730) per borrower, provided directly by banks to individuals; loans to distressed persons not exceeding INR 50,000 per borrower to prepay their debt to non-institutional lenders; loans to Self-help groups for agricultural and allied activities; loans sanctioned to state-sponsored organizations for scheduled castes and scheduled tribes for the specific purpose of purchase and supply of inputs.

fraudulent lending during elections. Specifically, we run the following regression:

$$\begin{aligned} y_{ijt} = \; & \beta_0 \text{Dual Election}_{j,(t+1)} \times \text{Deposit Concentration}_{ijt} \\ & + \beta_1 \text{Deposit Concentration}_{ijt} + \lambda_i + \theta_{jt} + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where i denotes bank, j denotes district, t denotes year, and y_{ijt} denotes the natural logarithm of total loans given by bank i in district j during year t. Deposit Concentration$_{ijt}$ denotes the deposit concentration of bank i in district j in year t. Dual Election$_{j,(t+1)}$ is equal to 1 if there is a state and federal election in year $t+1$. λ_i and θ_{jt} denote bank and district-year fixed effects, respectively. We cluster standard errors by state and year in all specifications.

5.1 Identifying Assumptions and Interpretations

The identifying assumption is that banks within the same district-year face similar lending opportunities. Hence, if banks with different deposit concentration exhibits different lending behavior, then it is not because they face differential demands for loans, but rather they are monitored differently by depositors.

In equation (1), the coefficient of interest is β_0. A negative β_0 suggests that depositor monitoring reduces bank fraudulent lending during electoral cycles. Formally, let $x_{0.75}$ ($x_{0.25}$) denote the 75th (25th) percentile of deposit concentration. Then, equation (2) ((3)) is the excessive lending made by concentrated (non-concentrated) banks during elections relative to non-election years. And the difference between equation (2) and equation (3) is the reduction in fraudulent lending due to depositor monitoring, which is given by $\beta_0(x_{0.75} - x_{0.25})$.

$$\begin{aligned} & \mathbb{E}\left[y_{ijt}|x_{0.75}, \text{Elect} = 1\right] - \mathbb{E}\left[y_{ijt}|x_{0.75}, \text{Elect} = 0\right] \\ = \; & \beta_0 x_{0.75} + \mathbb{E}[\theta_{jt}|\text{Elect} = 1] - \mathbb{E}[\theta_{jt}|\text{Elect} = 0] \end{aligned} \tag{2}$$

$$\begin{aligned} & \mathbb{E}\left[y_{ijt}|x_{0.25}, \text{Elect} = 1\right] - \mathbb{E}\left[y_{ijt}|x_{0.25}, \text{Elect} = 0\right] \\ = \; & \beta_0 x_{0.25} + \mathbb{E}[\theta_{jt}|\text{Elect} = 1] - \mathbb{E}[\theta_{jt}|\text{Elect} = 0] \end{aligned} \tag{3}$$

5.2 Measuring Deposit Concentration

Deposit Concentration$_{ijt}$ is measured as the ratio of total customer deposits (excluding deposits by founder depositors) to the number of depositors (excluding founder depositors). This measure is similar to the Herfindahl-Hirschman Index (HHI) and measures the average deposits per depositor. A bank with higher depositor concentration has higher average deposit per depositor, higher average depositor size and thus the depositors have a higher bargaining power over the bank. Figure 4 shows the summary statistics of this measure, where the unit of the measure is INR 10,000 per person. There is considerable heterogeneity in deposit concentration. The mean value is 0.21 and standard deviation is 0.13. The 99th percentile is 0.67 (interpreted as INR 67,000 per person), which is way below the deposit insurance limit of INR 100,000. This is consistent with previous studies on deposits in Indian banking system.[16]

5.3 Other Variables

We define other variables in Appendix B. Table 3 reports the mean of the key variables by quantiles of deposit concentration. We find that deposit concentration is positively correlated with bank size, total advances (including both priority and non-priority sector). It is negatively correlated with equity to assets ratio and non-performing loan (NPL) ratio. Other variables like net interest margin, return on advances and cost of funds do not vary significantly across different quantiles of deposit concentration.

6 Results

6.1 Electoral Cycle and Bank Lending

In this section, we provide empirical evidence that banks increase lending during dual elections and the increased lending is likely to be politically-motivated fraudulent lending.

[16] Iyer and Puri (2012) report a maximum account balance of INR 99,906 using data from a single cooperative bank from India. Agarwal et al. (2017) use data on the largest state-owned bank in India, and report that one needs to go at least 7 standard deviations above the mean to hit the deposit insurance limit.

Figure 5a shows the number of states with elections each year and Figure 5b shows the percentage of banks that were exposed to state election shocks each year. The number of states with elections is almost constant except for 2010. The percentage of banks exposed to state election shocks is similar across years except 2009 and 2010.

We then verify our conjecture that banks increase lending during dual elections and the increase in lending captures politically-motivated fraudulent lending. Figure 6a and 6b show that, during years of federal elections, 80% of cooperative bank credit is given to states with state elections (that happen in the same year as the federal election). While during other years, the number is less than 20%.

Table C.1 reports the regression results on cooperative bank lending in dual election periods. We regress log of advances on Dual Election$_{i,(t+1)}$ and cluster standard errors by state and year. In Table C.1, columns (1) to (6) use different combinations of controls and fixed effects. We find that the coefficient on Dual Election$_{i,(t+1)}$ is positive and significant at 1% level. The coefficient remains stable across all columns, and the model adjusted R^2 increases from 0.11 to 0.98 from column (1) to column (6). The results suggest that cooperative banks increase total credit by 15%-20% in periods of dual elections. Particularly, column (3) is a within-bank estimator, which compares the change in lending by a bank between periods of dual elections and other periods while controlling for state-specific business cycles.

In appendix C, we conduct further tests to show that the above results are not driven by an increase in demand for bank loans in regions with dual elections. We also examine the real effect of the increased lending during electoral cycles and don't find any significant effect on real economic activity. Finally, we perform a placebo test to rule out any mechanical relationship between bank lending and the electoral cycle.

6.2 Bank Fraudulent Lending and Depositor Monitoring

In this section, we present robust evidence that depositor monitoring reduces bank fraudulent lending during election years. Figure 7 plots bank lending as a function of deposit concentration for years with dual election and years without dual election. Banks with high deposit concentration reduce lending in dual election years while banks with low deposit concentration increase lending. This is consistent with our story that big depositors monitor banks more closely and thus reduce bank fraudulent lending.

6.2.1 Baseline Results

Using the specification in equation (1), we test whether depositor monitoring reduces bank fraudulent lending during elections. We report the results in Table 4. The point estimate on Dual Election$_{j,(t+1)}$ $\times$ Deposit Concentration$_{ijt}$ is negative and statistically significant across all specifications. While the point estimate is relatively stable in columns (1) to (5), it drops significantly from column (5) to (6) after we add bank fixed effects. We believe this is evidence for ex-ante selection by big depositors into "better" banks, e.g. banks with less political connection or other unobserved characteristics. Bank fixed effects absorb these unobserved bank-specific characteristics. On a conservative note, a bank with deposit concentration at the third quartile reduces fraudulent lending by 2.5% relative to a bank with deposit concentration at the first quartile[17].

We then conduct a series of robustness tests to address the concerns over omitted variable bias, spurious correlation, and our results being driven by uninsured depositors or demand shocks.

In Table 5, we control for time-varying bank characteristics, and the results are qualitatively similar to table 4. Table 6 shows that the results are robust to an alternative measure of bank lending, $\frac{\text{Advances}_t}{\text{Assets}_{t-1}}$.

To rule out the possibility that our results are driven by other unobserved time-varying bank characteristics correlated with our measure of deposit concentration, we conduct the test of omitted variable bias proposed in Oster (2019) and Altonji, Elder and Taber (2005)[18]. The identified set for our specification is $[0.1812, 0.1664]$. Since zero is not included in this identified set, we can reject the null hypothesis that our point estimate is driven by omitted variables. We computed this identified set by assuming the strength of unobservables relative

[17] The number is computed as follows. Bank with deposit concentration at the third quartile makes fraudulent lending $f\left(D_{0.75}\right)=\mathbb{E}\left[y_{ijt} \middle| Elec_{jt}=1, DepConc_{ijt}=D_{0.75}\right]-\mathbb{E}\left[y_{ijt} \middle| Elec_{jt}=0, DepConc_{ijt}=D_{0.75}\right]=\beta_0 D_{0.75}=-0.1812\cdot 0.268$. Bank with deposit concentration at the first quartile makes fraudulent lending $f\left(D_{0.25}\right)=\beta_0 D_{0.25}=-0.1812\cdot 0.127=0.202$. The difference is $f\left(D_{0.75}\right)-f\left(D_{0.25}\right)=\beta_0\left(D_{0.75}-D_{0.25}\right)=-0.1812\cdot(0.268-0.127)=-0.0255$.

[18] We provide details of this test in appendix D.

to observables is 1. Alternatively, we can estimate the relative strength of unobservables relative to observables required such that zero is included in the identified set. We estimate the relative strength to be 12.2. As the model R^2 is around 98% we argue that this estimate of 12 is economically implausible. In addition, we conduct a simple kitchen-sink analysis to test if the interaction term of deposit concentration and dual election gains statistical significance via its correlation with the interaction term of observed bank covariates with dual election. Table 7 reports these results. The point estimate of the interaction term of deposit concentration and dual elections is statistically significant among all specifications from columns (1) to (7) and is similar in magnitude to the baseline estimates reported in column (8) of Table 4.

We also conduct a placebo test to verify that our results are not just spurious correlation between deposit concentration and bank lending. We create a placebo Dual Election variable by assuming that each state-year has a 0.2 probability to have a dual election[19]. We generate 3,500 such placebo Dual Election series, and for each simulated series we run the baseline regression in equation (1). Figure 8 plots the distribution of the point estimates of β_0 from the 3,500 Monte Carlo simulations. We see that the distribution is close to normal with a small positive mean of 0.002. Besides, the point estimate of -0.1812 reported in column (8) of Table 4 is lower than the 1st percentile (-0.151) in the distribution. This indicates that our point estimate is observed less than 1% times, and thus we can reject the null hypothesis of spurious relationship at 99% level of confidence.

Next, we address the issue of our results being driven by big depositors that are not fully insured. We take the average of deposit concentration for each bank during our sample period, and then categorize the banks into four groups by the average deposit concentration: (1) less than or equal to 25th percentile value, (2) greater than 25th and less than or equal to 75th percentile value, (3) greater than 75th percentile and less than or equal to 95th percentile, and (4) greater than 95th percentile value. We estimate our baseline specification and report the point estimates (with 95% confidence intervals) for each group in Figure 9. The incremental lending during election years monotonically declines with deposit concentration. Moreover, uninsured depositors are likely to be concentrated in higher buckets

[19]The probability of 0.2 is based on the empirical probability observed in the data.

of deposit concentration. Given that our results are not driven by banks with the highest deposit concentration, we can rule out the possibility that our results are primarily driven by uninsured depositors.

A valid concern is that the reduced lending in concentrated banks could reflect a decreasing demand for loans by households or firms. For example, expansionary fiscal policy (Alesina, Cohen and Roubini (1992)) could decrease the demand for loans. Besides, during elections, we often see high uncertainty and low firm investment (Jens (2017)). This could decrease the demand for bank loans by firms. Both these explanations should indicate an overall decline in lending. However, there is not a priori reason to believe that aggregate uncertainty would result in a differential demand response within the cross-section of banks. Moreover, by adding district-time fixed effects, we can control for such aggregate shocks to demand.

Finally, one may argue that since one of our major federal elections coincides with the global financial crisis of 2008, and it is the global financial crisis rather than the elections that drives bank lending cycles. However, the global financial crisis did not exert any significant impact on cooperative banks. After a dip in 2008, deposit and credit growth both rebounded in 2009. While (real) credit growth declined to 2% in 2009 from nearly 6.5% in 2008, it quickly recovered to nearly 9% by 2009. Deposit growth also improved to over 10% in 2010 from 7% in the previous year. The 2009 and 2010 Reserve Bank of India report suggests that the cooperative banks remained significantly resilient to the financial crisis. The Indian experience of cooperative banks during the crisis is consistent with the documented resilient response of cooperative banks during the crisis, both in Europe (Henselmann, Ditter and Lupp (2016)) and elsewhere (International Labour Office (2013)).

6.2.2 Results by Types of Loans

We run the baseline specification in equation (1) for different types of loans. Table 8 presents the results. Column (1) and (2) report results for priority sector lending (PSL) and non-priority sector lending (Non-PSL). The results indicate that there is a greater lending reduction in Non-PSL than PSL. A unit increase in deposit concentration reduces Non-PSL (PSL) by 16% (10%) during election years relative to non-election years.

We then examine fraudulent lending within the priority sector. Columns (3)-(6) show the lending to agriculture, small scale industries, medium and large scale industries and other priority sectors, respectively. We find that the reduction in PSL is driven by small scale industries. And the reduction in small scale industries is comparable to that in Non-PSL. However, we don't see a reduction in fraudulent lending to other priority sectors, though these sectors account for a very tiny portion of PSL.

The results for small scale industries seem to contradict Cole (2009), who finds that fraudulent lending during electoral cycles is mainly driven by lending to the agriculture sector. There are two explanations for this. First, Cole (2009)'s sample include both rural and urban banks while our sample only consists of urban cooperative banks. Second, Cole (2009) focuses on commercial banks which have a 60% sub-target of agriculture lending within the overall PSL target. There is no such sub-target for agricultural lending among cooperative banks, instead there is a sub-target for lending to small scale industries.

6.3 Asset Quality, Profitability and Deposit Monitoring

If banks with low deposit concentration do more fraudulent lending than those with high deposit concentration, then we should observe two results. First, banks with low deposit concentration should see their asset quality going down post-election. Second, they should also have lower return on advances. Table 9 shows the non-performing loan (NPL) ratio in period $t+1$ as a function of deposit concentration and election in year t. Consistent with our hypothesis, we find that the coefficient on the interaction of deposit concentration and dual election is negative and statistically significant. On a conservative note, our results indicate a 0.8% lower NPL ratio after dual election for banks at the third quartile of deposit concentration relative to banks at the first quartile.

We then examine NPL ratio over longer horizons. Specifically, we conduct a Jordà (2005) local projection to examine the NPL ratio in one, two, three and four years after the dual election. The results are reported in Table 10. Consistent with the results reported in Table 9, we find a negative and significant point estimate of the interaction term. The point estimate in column (3) is negative though insignificant. This insignificance could potentially be driven by the low power of the test due to the decrease in the number of observations when we move from column (2) to (3). The results indicate that increased lending by low-deposit-concentration banks results in lower asset quality relative to high-concentration banks. Moreover, the lower asset quality is persistent for at least the next four years following the dual election.

We also test the predictions bank profitability, as measured by return on advances. In Table 11, column (1) ((2)) reports the regression of the return on advances one year (two years) after the dual election on the interaction term of deposit concentration and dual election. The point estimate is positive and statistically significant. Compared to low-deposit-concentration banks, high-deposit-concentration banks enjoy a 0.6% higher return on advances in the year following the election despite their reduction in lending.

An alternative explanation for the above results is that banks with different levels of deposit concentration have different net interest margins or cost of funding. To rule out these two alternative stories, we run a specification similar to column (1) in Table 11 by replacing the dependent variable with net interest margin or cost of funds. The results are in columns (3) and (4), respectively. We fail to reject the null hypothesis of zero point estimates on the interaction term for both columns (3) and (4). This indicates that the return on advances is not driven by different supply side exposure of banks with different levels of deposit concentration.

Taken together, lower NPL ratio and higher return on advances in high-deposit-concentration banks suggest that the decreased lending in these banks is associated with better asset quality and higher profitability.

6.4 Exit as a Punishing Device

So far we have empirically documented the selection and voice mechanism of depositor monitoring. In this section, we present evidence on the exit channel. We estimate the following model:

$$\begin{aligned} y_{ijt} &= \alpha_i + \beta_0 NPL_t \times \text{Deposit Concentration}_{t-1} \\ &\quad + \beta_1 NPL_t + \beta_2 \text{Deposit Concentration}_{t-1} + X_{ijt} + \theta_{jt} + \epsilon_{ijt} \end{aligned}$$

where α_i denotes bank fixed effects, θ_{jt} denotes district-year fixed effects, X_{ijt} denotes time-varying bank specific covariates and y_{ijt} denotes the natural logarithm of customer deposits. The coefficient of interest is β_0. Our depositor monitoring mechanism suggests that big depositors punish banks more when asset quality decreases, which implies that $\beta_0 < 0$.

We report the results in Table 12. As hypothesized, we find that the point estimate on the interaction term of NPL ratio and deposit concentration is negative and statistically significant. Our most conservative point estimate in column (7) indicates that for a 1% increase in NPL ratio, banks at the third quartile of deposit concentration experience 10% higher deposit outflows than banks at the first quartile of deposit concentration. Similarly, a reduction in NPL ratio is associated with a greater reward by big depositors. Hence, big depositors punish (reward) banks for poor (good) performance more than small depositors.

6.5 Bank Fragility and Deposit Concentration

The results in Table 12 suggest that big depositors threat to withdraw from banks that perform poorly and make these banks more fragile. Diamond and Rajan (2001) point out that the fragility of banks commits them to create liquidity, making such banks ex-ante safer. In this section, we formally test this argument.

First, we examine whether deposit concentration is related to bank health measured by non-performing loan ratio (NPL) or bank failure. Figure 10 and 11 show that NPL ratio or bank failure is negatively correlated with deposit concentration, which is consistent with Diamond and Rajan (2001).

Then we run a linear probability model of bank failure on deposit concentration. The results are reported in Table 13. The dependent variable is equal to 1 if the bank fails in year $t + 1$ and 0 otherwise. Our results indicate that higher deposit concentration is associated with lower probability of bank failure. Moving from the first quartile to the third quartile of deposit concentration, we see a 1.5% reduction in the probability of bank failure. These results suggest that monitoring by big depositors makes banks fragile and hence ex-ante safer, even in the presence of deposit insurance.

6.6 What Explains the Heterogeneity in Deposit Concentration?

To understand the factors that explain the heterogeneity in deposit concentration among banks, we document how much of this cross-sectional variation can be attributed to observed versus unobserved bank characteristics.

Table 14 reports these results. The natural logarithm of the book value of firm assets explains $\approx 20\%$ of the variation in deposit concentration, Banks' equity to assets ratio explains 3% of variation in deposit concentration. Other bank-specific covariates such as return on advances, net interest margin, cost of funds and other income to assets ratio explain less than 1% of the variation in deposit concentration. Banks' non-performing loan ratio explains $\approx 8\%$ of the variation in deposit concentration. All observed bank-specific covariates together explain a total of 27% variation in deposit concentration. Addition of bank and district-time fixed effects increases the model R^2 from 27% to 87%. In total, observed and unobserved bank-specific characteristics explains 87% of variation in deposit concentration among banks.

6.7 Self-dealing Founder Depositors and Non-Founder Depositors

A cooperative bank has two groups of depositors – founder depositors and non-founder depositors. The conflict of interest between them incentivizes non-founder depositors to monitor the bank. On the other hand, non-founder depositors may also collude with founder depositors into self-dealing. In this section, we examine whether such collusion is present in cooperative banks.

Founder depositors in cooperative banks are effectively "insured" equity holders. They establish cooperative banks by pooling their initial deposits and they hold equity stakes in the bank which are proportional to their initial deposits. So the initial investment by founder depositors are considered as deposits but recorded as equity in banks' books, and thus insured by the deposit insurance. When the bank is operating, these founder depositors receive dividends from banks, and when the bank fails they are not residual claimants as their deposits are insured. This equity structure in cooperative banks is distinctive from that prevalent in Myers (1977), where equity is the residual claimant.

This creates an inherent tension in the incentives of founder depositors. On one hand, they receive dividends from good-performing banks and on the other could also engage in riky fraudulent lending as their investment is safe in case of bank failure. Allen, Carletti and Marquez (2011) show how banks may costly hold capital to reduce the premium demanded by depositors, as it forces banks to commit to monitoring and gives borrower higher surplus. Jiménez et al. (2014) and Dell'Ariccia, Laeven and Suarez (2017) provide evidence of reduced risk-taking in highly capitalized banks. These papers all document equity as a device to monitor banks. But when equity is riskless (in the case of founder depositors of cooperative banks), equity no longer acts as a monitoring device. And even worse, anecdotal evidence suggests that founder depositors directly involve in most cooperative bank fraud scandals in India.[20] If founder depositors collude with non-founder depositors in doing fraudulent lending, then non-founder depositors could also benefit from fraudulent lending.

We test whether there is collusion between founder and non-founder depositors and present the results in Table 15. We regress bank lending on the triple interaction term of deposit concentration, equity to assets ratio and dual election. Consistent with our baseline results, the coefficient on the interaction of deposit concentration and dual election is negative and statistically significant. The point estimate of the interaction term of equity to assets ratio and dual elections is also negative and statistically significant. The negative point estimate is consistent with conventional monitoring roles of equity. The triple interaction term is however positive. This indicates that bank lending rises during the period of elections relative to non-election years for banks with high deposit concentration and high bank equity. This is consistent with the idea of non-founder depositors collude with founder depositors to extract benefits from fraudulent lending.

[20]National Bank for Agriculture and Rural Development (NABARD) recently accused the local legislator of financial management in the cooperative bank founded by him (The Economic Times (2018)). In another case, 11 founder depositors including MD of the Adarsh Co-operative Society Limited (ACCSL) were arrested for allegedly siphoning off more than INR 1,400 Cr ($\approx$ \$ 200 mn) of investors funds (The Hindustan Times (2019)). During the recent demonetization episode in India, cooperative banks' founder depositors were accused of using these banks to funnel unaccounted cash The Hindu (2019).

7 Conclusion

We present empirical evidence that depositors monitor banks even when deposits are insured. Using a representative sample of Indian cooperative banks, we find that banks with big depositors engage in less fraudulent lending, have higher asset quality and exhibit better performance than those with small depositors. Banks with big depositors are also more vulnerable to runs, which in turn makes them safer ex ante.

Our results support a depositor monitoring mechanism that involves depositor selecting banks ex ante, voicing their concerns to banks and exiting banks if their voices are ignored. These three forces form the cornerstones of depositor monitoring mechanism. Non-pecuniary benefits to depositors and incomplete deposit insurance incentivizes depositors to discipline banks and improve bank asset quality, even when deposits are insured.

Moreover, we document an increase in fraudulent lending when big depositors with perverse motives engage in a relationship with self-dealing equity holders. This result can be exploited by regulatory and other monitoring authorities to detect banks' fraudulent behavior. Our results of politically-motivated lending during simultaneous federal and state elections inform the policy debate on formally re-linking the two elections in India. Relinking of the two elections has recently gained momentum in India (Parliamentary Standing Committee Report (2015)) and our results show the negative effects of simultaneous elections in terms of bank fraudulent lending.

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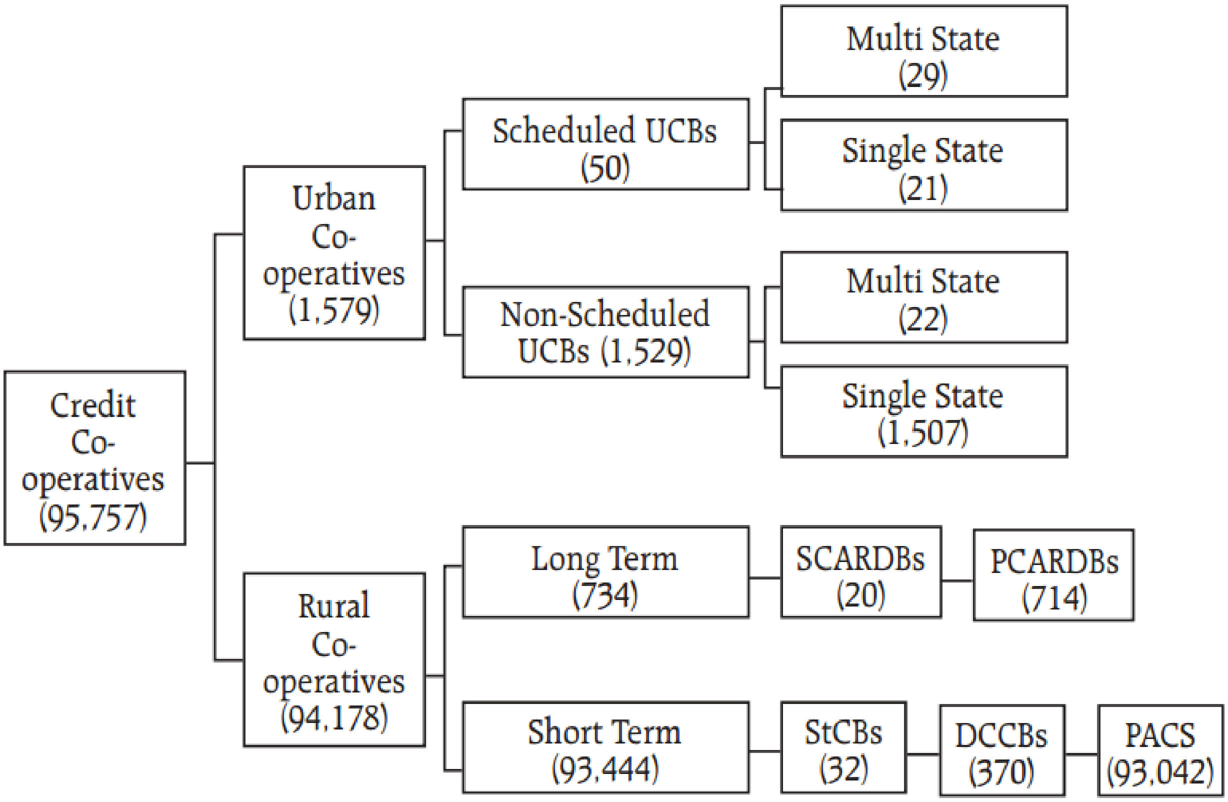
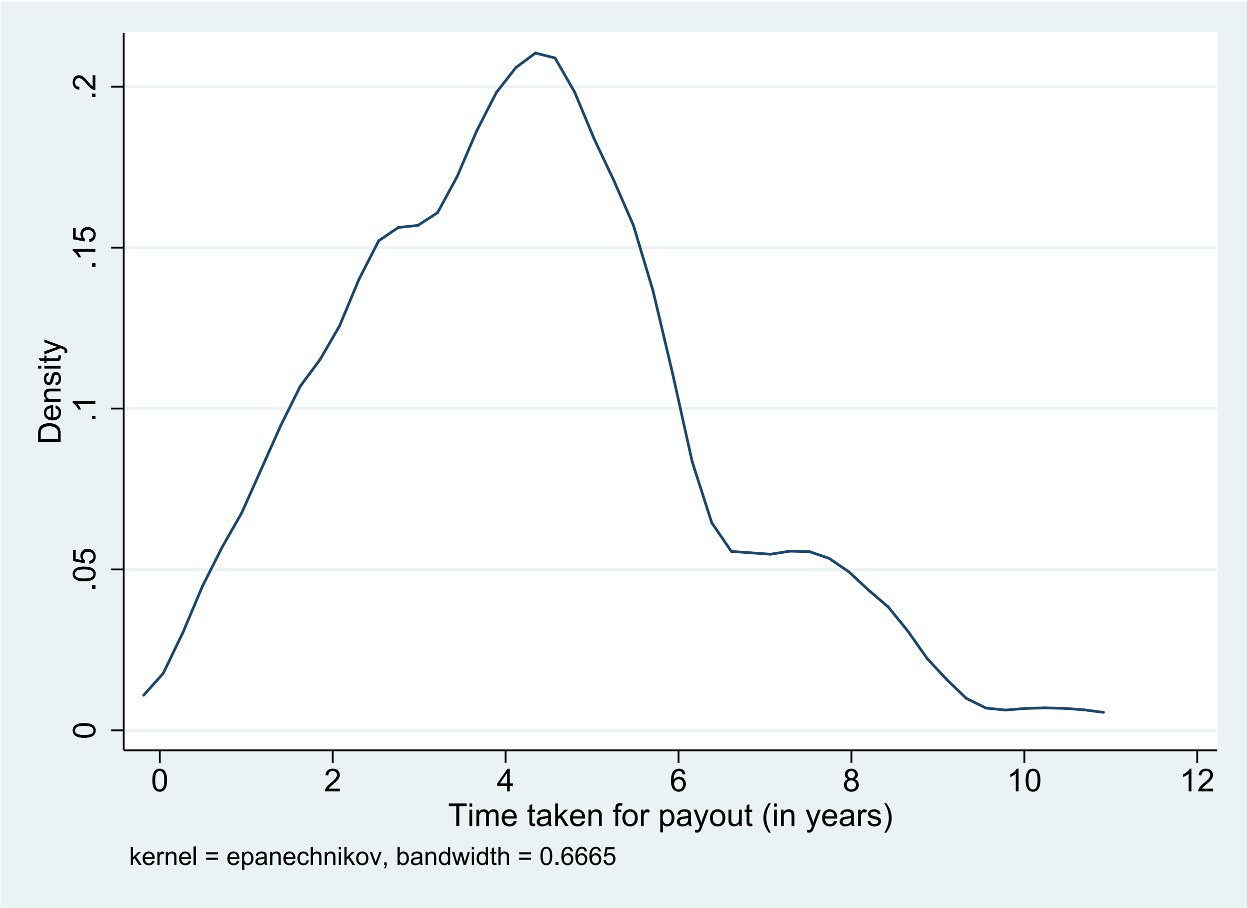
Figure 1: Cooperative Banking Structure in India



Source: Report on Trends and Progress of Banking in India 2012-13

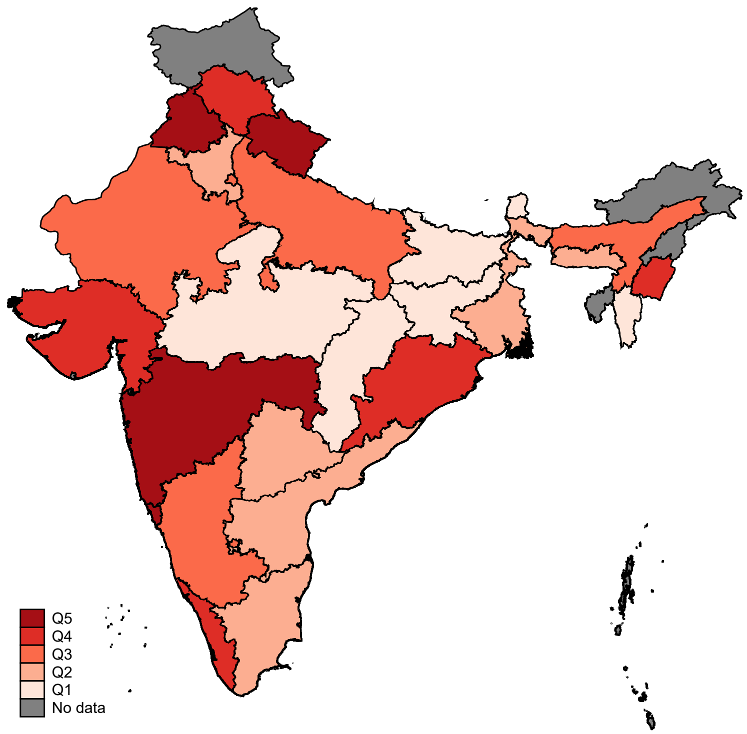
Figure 2: Time to Payout (in years)



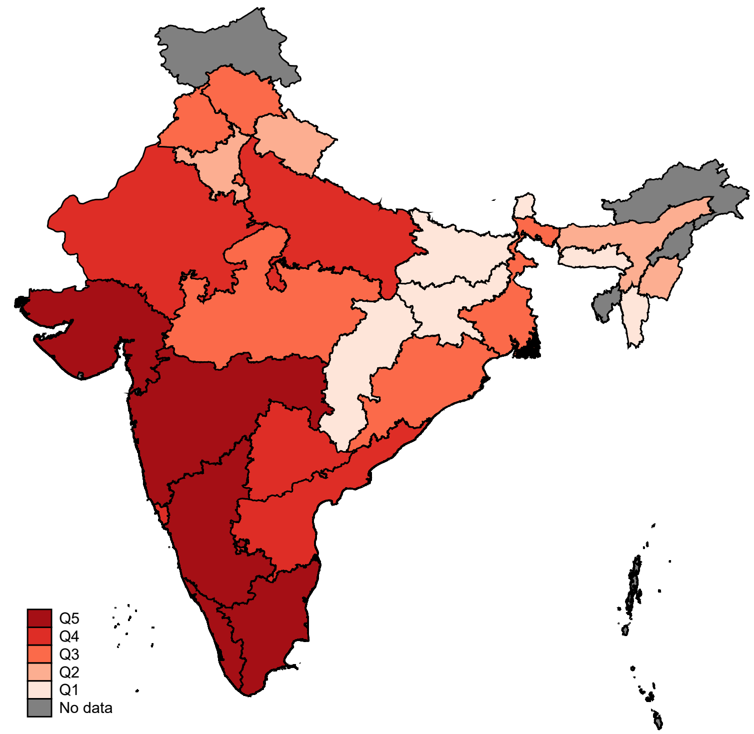
p1	p5	p25	p50	p75	p95	p99	Mean	St Dev
0.480	1.400	2.790	4.225	5.140	7.960	10.250	4.213	1.999

The figure plots the kernel density of time to payout (in years). For each bank failure between 2006 and 2013, we identify the time required to payout conditional on payout.

Figure 3: State-wise Cooperative Bank Lending in India.



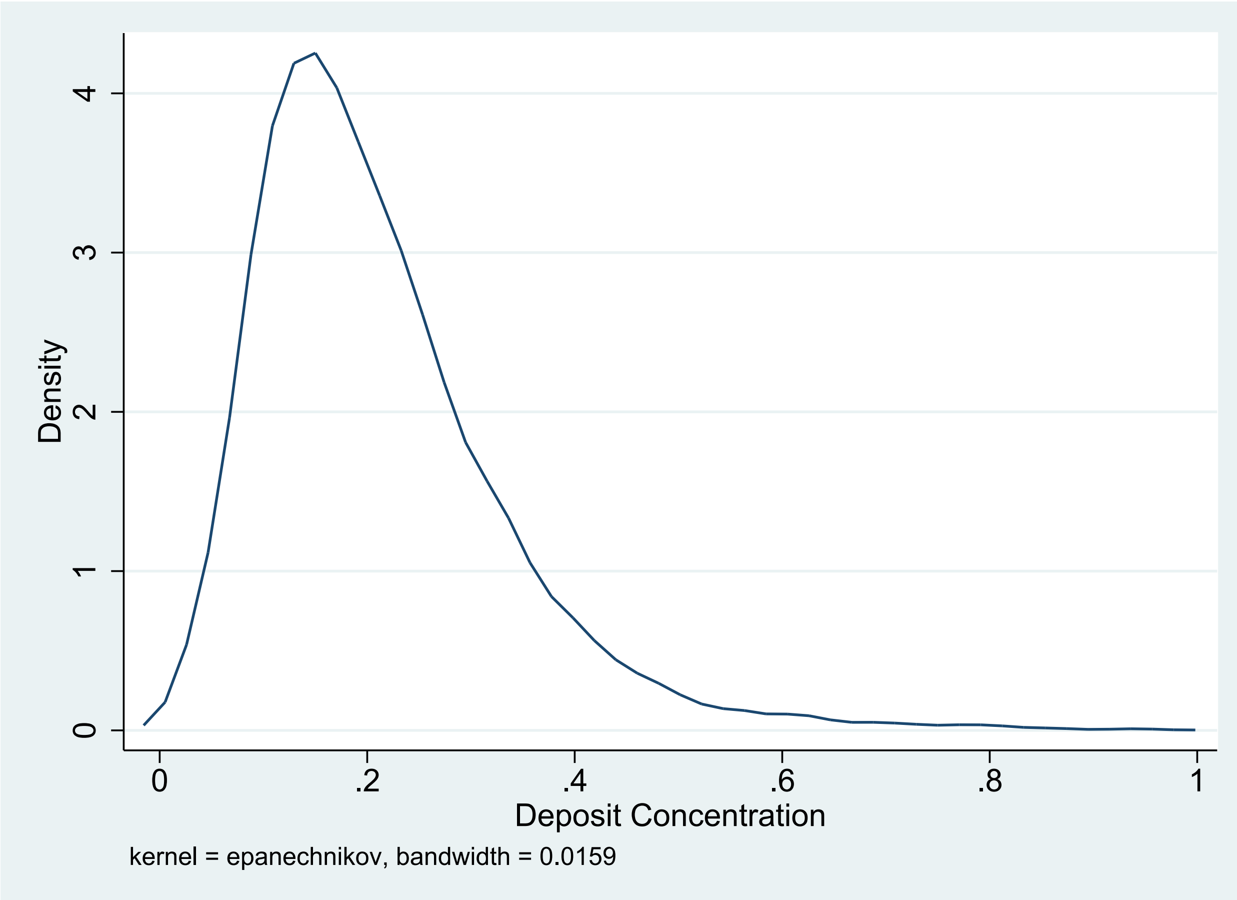
(a) Average Cooperative Bank Lending



(b) Share of Cooperative Bank Lending

The figure shows the heat map of the distribution of total advances by cooperative banks at the state level. Panel A shows the average lending for the period 2006 to 2013. Panel B shows the average share of lending to a state relative to total lending for the period 2006 to 2013. The figure has been created uses data on cooperative bank lending by 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The scale runs from light red for smaller values to dark red for bigger values. Each colour depicts a quantile of the data. The map has been developed using open source software and used only for presentation purposes. The actual geographical boundaries are not confirmed.

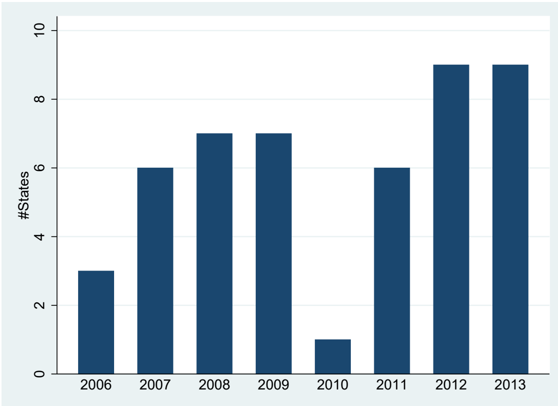
Figure 4: Kernel Density of Deposit Concentration



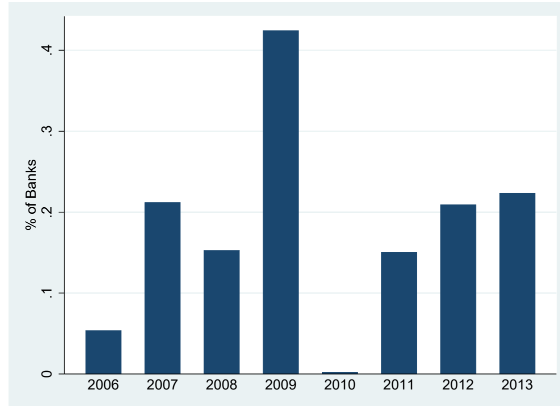
p1	p5	p25	p50	p75	p95	p99	Mean	St Dev
0.0329	0.0671	0.1268	0.1863	0.2678	0.4363	0.6684	0.2129	0.1291

The figure plots the kernel density of deposit concentration. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors in the bank. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The table underneath the figure gives the numbers associated with the distribution plotted in the figure. 4

Figure 5: Source of Identification



(a) Number of States with Elections



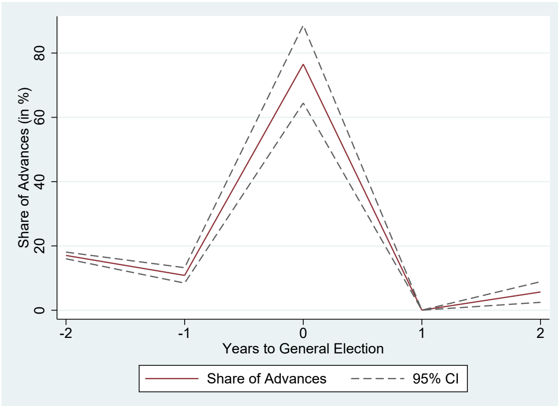
(b) Share of Banks in States with Elections

The figure shows the number of states facing state elections and the share of banks located in states facing state elections. The left panel shows the number of states that faced state-level elections in the dataset. The right panel shows the share of banks located in states that faced state elections in the dataset. Share of banks is calculated as follows:

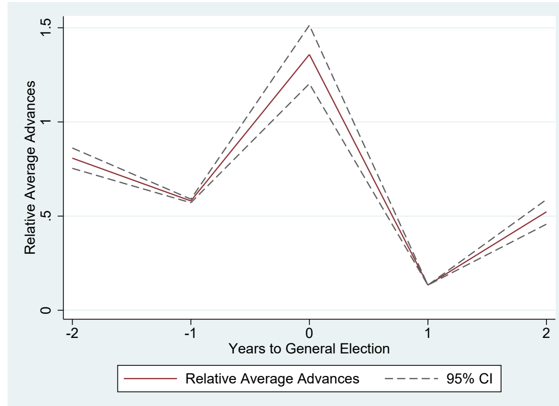
$$\text{Sh\_Bank}_t = \frac{\sum_{j=1}^{N} \text{Number of banks in State j}_t \mathbb{1}(\text{S\_Elect}_{j,t+1} = 1)}{\sum_{j=1}^{N} \text{Number of banks in State j}_t}$$

The figure has been created uses data on cooperative bank lending by 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013.

Figure 6: Cooperative Bank Loans and Electoral Cycle



(a) Share of Advances



(b) Relative Average Advances

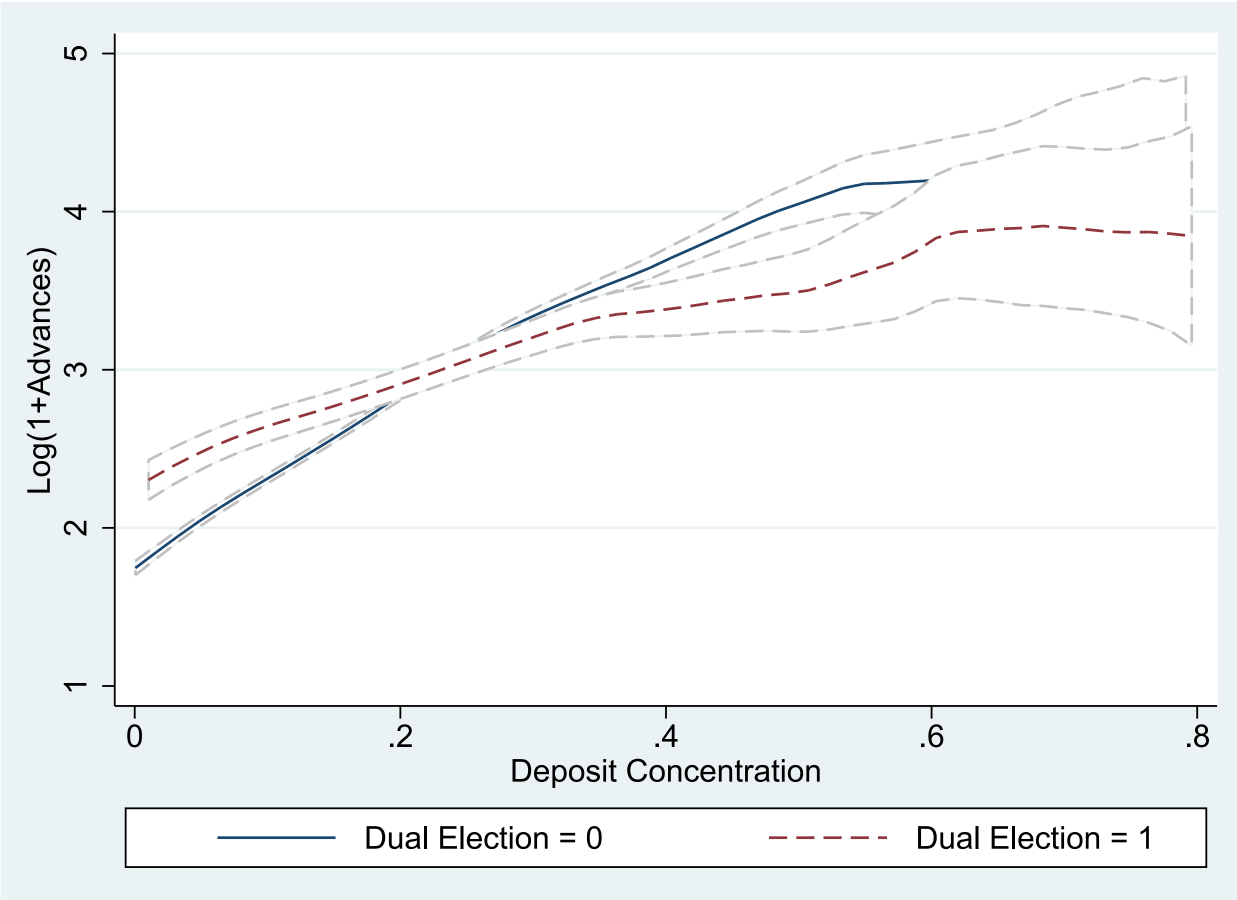
The figure shows the share of advances and relative average advances made by cooperative banks in states that had a state election. These are measured as follows:

$$\text{Share}_t = \frac{\sum_j [\text{Loans}_{j,t} \mathbb{1}(S\_Elect_{j,t+1} = 1)]}{\sum_j \text{Loans}_{j,t}}$$

$$\text{Relative Average}_t = \frac{\sum_j [\text{Loans}_{j,t} \mathbb{1}(S\_Elect_{j,t+1} = 1)] / \sum_j \mathbb{1}(S\_Elect_{j,t+1} = 1)}{\sum_j \text{Loans}_{j,t} / \sum_j 1}$$

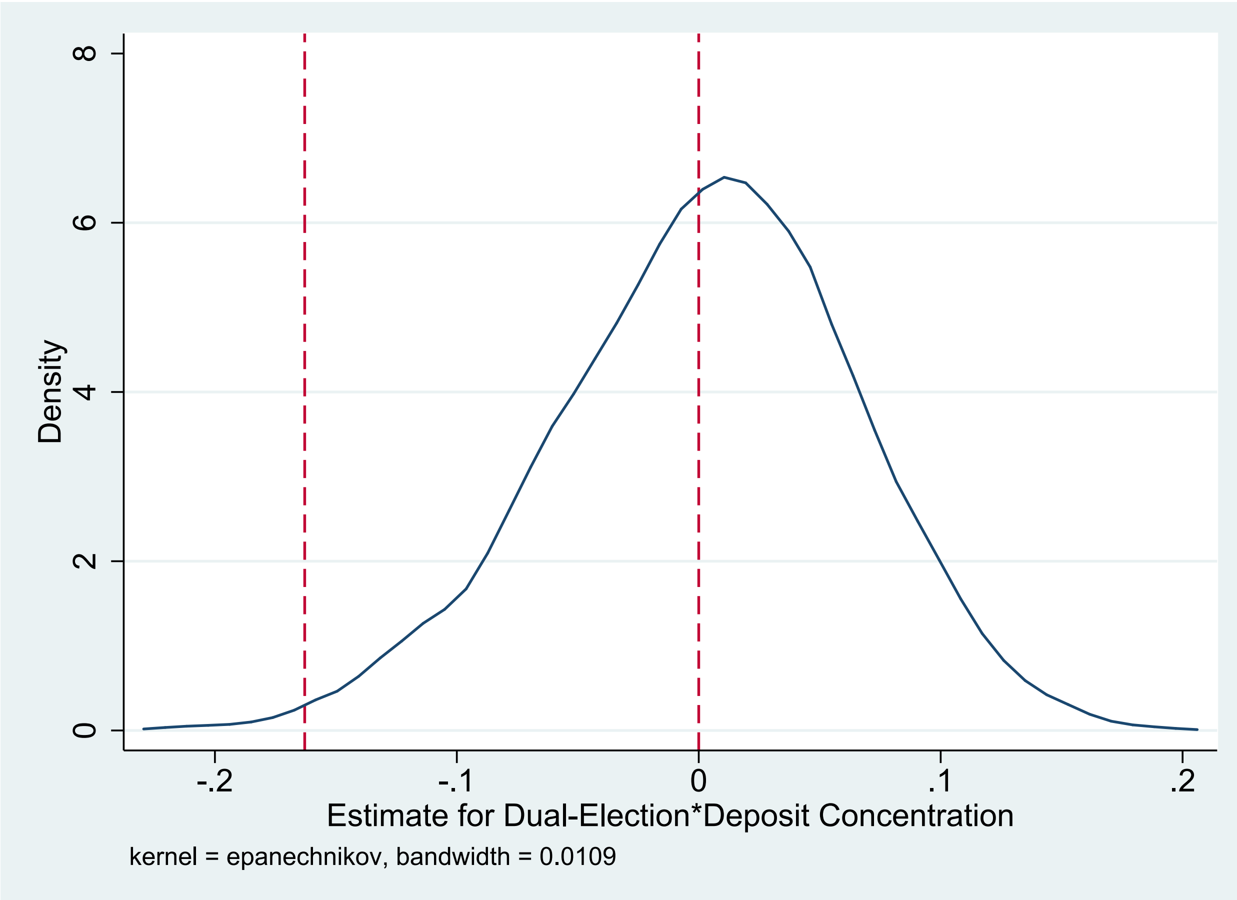
Share of advances is measured by the ratio of total advances made in states with state election in the next year to the total advances made by cooperative banks in that year. The relative share of advances gives the average loan advanced in states with state election next year relative to average credit extended in all states in that year. Panel A reports the share of advances and panel B reports the relative average of advances in percentage values. The figure has been created using data on cooperative bank lending by 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. All continuous variables are winsorized annually at 1%.

Figure 7: Deposit Concentration, Bank Lending and Dual Elections



The figure plots the local polynomial function of bank lending against deposit concentration. The blue solid line plots the bank lending as a function of deposit concentration during non-dual election years. The red dashed line plots bank lending as a function of deposit concentration during dual elections years. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. All continuous variables are winsorized annually at 1%.

Figure 8: Placebo Test



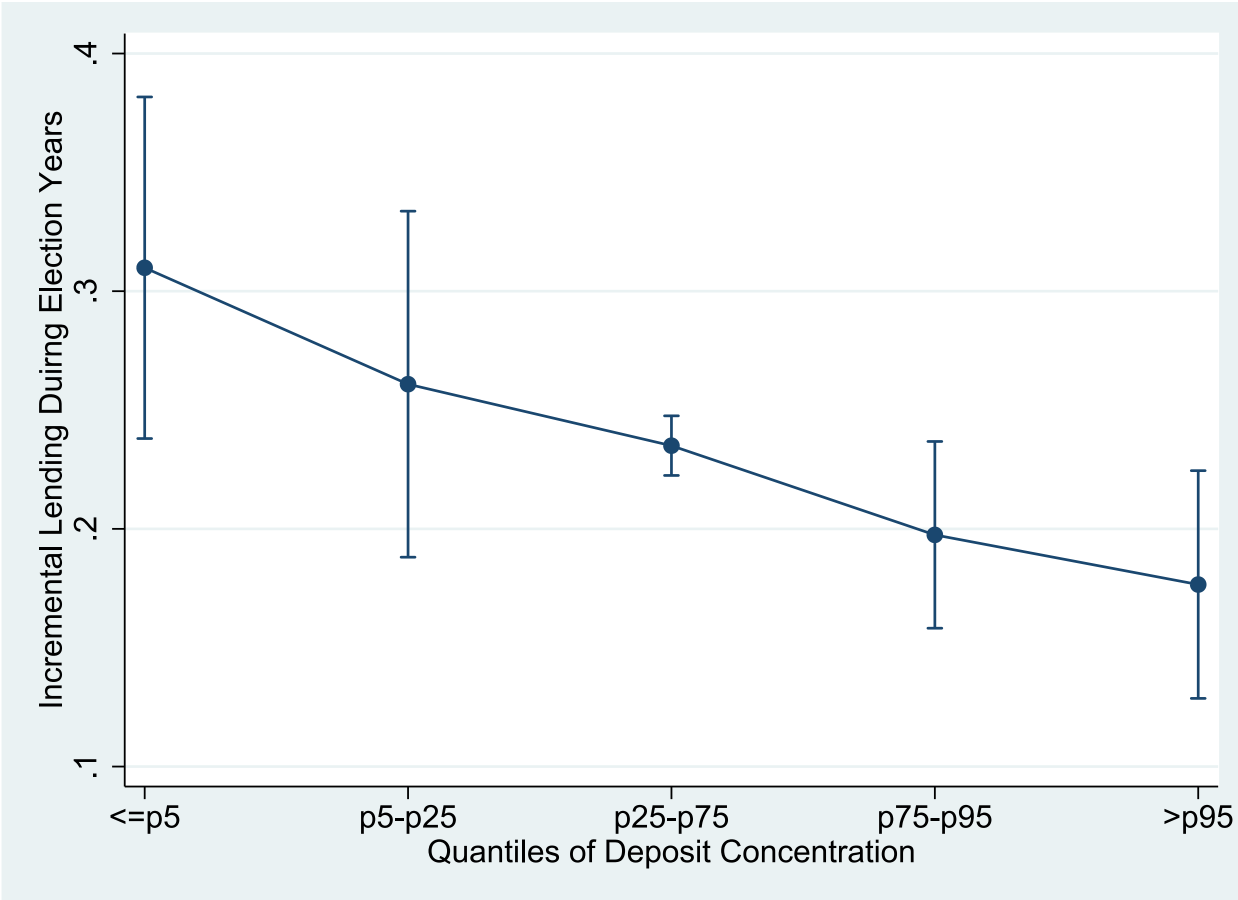
Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	St Dev
-0.219	-0.151	-0.107	-0.038	0.006	0.045	0.101	0.139	0.195	0.002	0.062

The figure plots the kernel density of the point estimates of the Dual Election*Deposit Concentration obtained from the 3,500 Monte Carlo simulations. We generate a new Dual Election variable for each state in every simulation by assigning the probability that each state-year faces a dual election to be 0.2. We call this new dual election year as placebo dual election year. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of one plus credit. α_i and θ_{jt} denotes the bank and district-year fixed effects.

$$y_{ijt} = \gamma \text{Placebo Dual Election}_{j,t+1} * \text{Dep-Conc}_{it} + \gamma_1 \text{Dep-Conc}_{it} + \alpha_i + \theta_{jt} + \epsilon_{ijt}$$

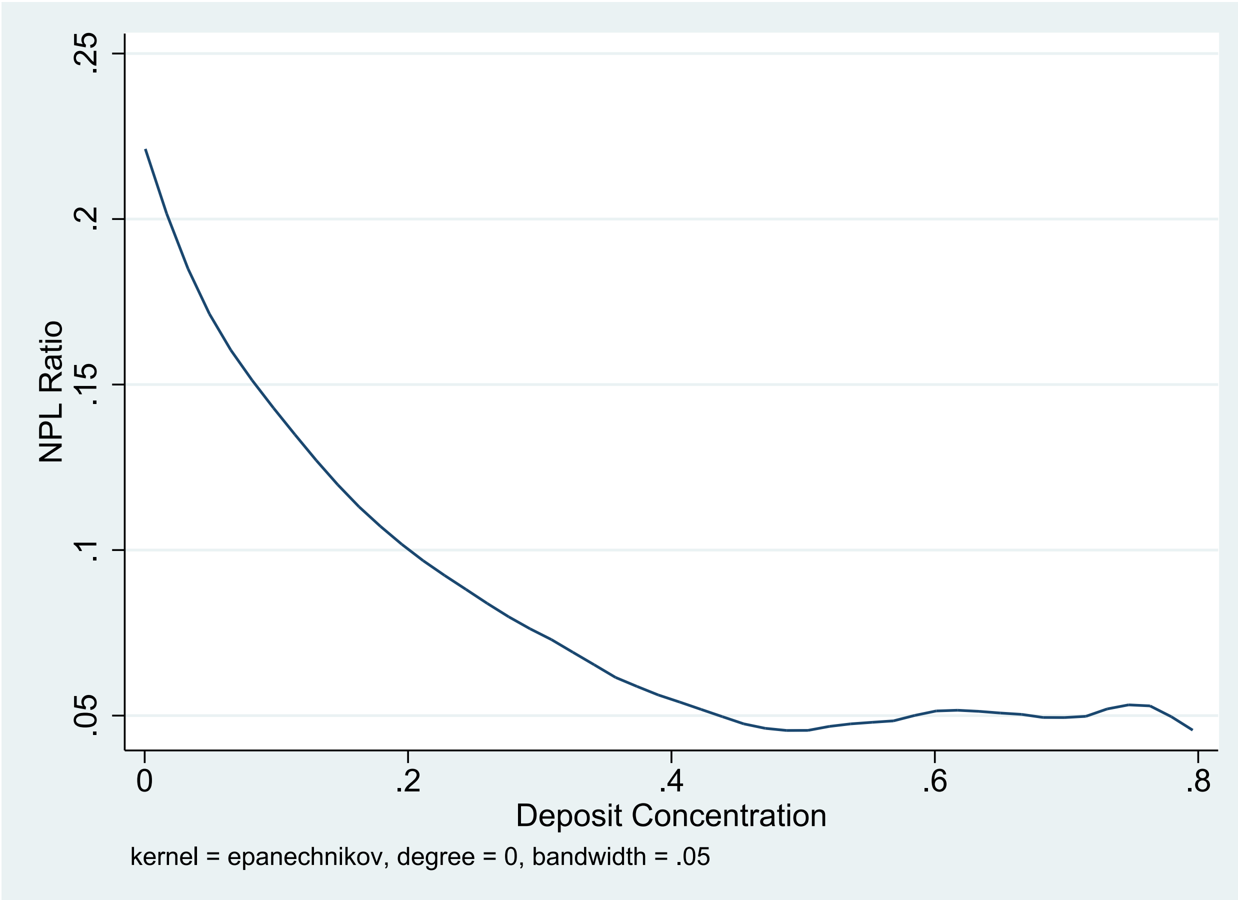
Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%. The table underneath the figure gives the numbers associated with the distribution of the estimates plotted in figure 8. We are able to reject the null of zero point estimate about 12.8% time under a one-sided test and 17.8% times under a two-sided test. The red vertical lines mark the value of 0 and -0.17. The mass to the left of -0.17 is 0.5%.

Figure 9: Incremental lending during Election Years by Buckets of Deposit Concentration



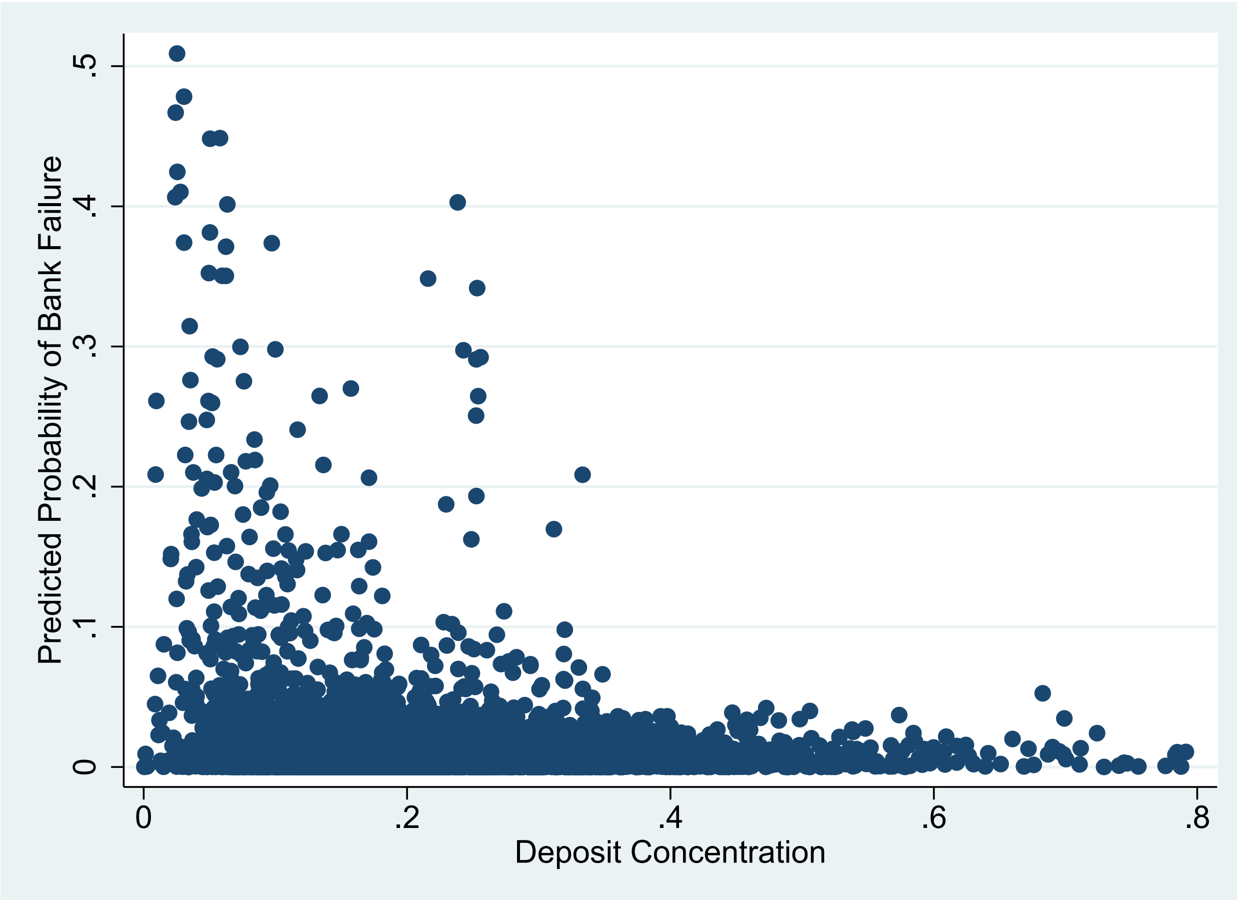
The figure plots the point estimates and the 95% confidence intervals of the interaction terms of different buckets of deposit concentration and dual election. Each point estimate measures the incremental lending in a district during election years relative to non-election years for different buckets of deposit concentration. Deposit concentration is measured as the average of deposit concentration for each bank during our sample period. We split this average measure into four buckets: (1) less than equal to 25th percentile value, (2) greater than 25th and less than equal to 75th percentile value, (3) greater than 75th percentile and less than equal to 95th percentile, and (4) greater than 95th percentile value. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013.

Figure 10: Deposit Concentration and Non-Performing Loan Ratio



The figure plots the local polynomial function of non-performing loan ratio against deposit concentration. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. All continuous variables are winsorized annually at 1%.

Figure 11: Bank Failure and Deposit Concentration



The figure reports the scatter plot of the predicted probability of bank failure and deposit concentration. We predict the probability of bank failure using a probit model controlling for bank level and district level factors. Bank level factors include size, equity to assets ratio, net interest margin, cost of funds, return on advances, non-performing loan ratio, portfolio of loans. District level variables include growth rate in district GDP and rainfall. We also use region-specific trends. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. All variables are winsorized annually at 1%.

Table 1: Description of Sample

Year	Whole sector				Sample			
	UCB	Asset	Sch. UCB	Asset	UCB	Asset	Sch. UCB	Asset
2004	1,919	23	55	11.4	57	11.2	50	11.1
2005	1,982	28	55	12.8	168	17.9	53	12.7
2006	1,853	32	55	14.6	242	22.0	54	14.0
2007	1,813	39	53	17.3	340	27.3	53	16.9
2008	1,770	41	53	17.2	891	34.8	53	16.2
2009	1,721	41	53	17.7	1,315	38.2	53	17.3
2010	1,674	52	53	22.7	1,403	47.9	53	22.4
2011	1,645	59	53	25.6	1,461	54.3	53	25.2
2012	1,618	57	52	26.6	1,444	54.0	52	26.1
2013	1,606	58	51	26.0	1,392	55.0	51	25.7

The table reports the comparison of the total population of urban cooperative banks in India to the sample of urban cooperative banks considered in the study between 2004 and 2013.

Table 2: Summary Statistics of the Sample

Variables	# Obs	p25	p50	p75	Mean	St. Dev
Ln(1+Adv)	7,063	1.893	2.656	3.648	2.845	1.296
Ln(1+PSL)	7,059	1.653	2.378	3.290	2.543	1.200
Ln(1+Non-PSL)	7,063	0.457	1.413	2.509	1.646	1.407
Ln(1+Agriculture)	7,059	0.000	0.062	0.768	0.512	0.788
Ln(1+SSI)	7,059	0.000	0.164	1.065	0.740	1.128
Ln(1+Other PSL)	7,059	0.000	0.043	0.630	0.450	0.731
Ln(1+M&L)	7,059	0.000	0.000	0.000	0.154	0.586
NIM	7,091	0.024	0.032	0.040	0.031	0.016
RoAdv	7,091	0.153	0.175	0.205	0.179	0.082
CoF	7,091	0.055	0.067	0.076	0.063	0.026
NPL	7,091	0.031	0.071	0.133	0.108	0.130
Ln(Asset)	7,091	1.303	1.661	2.114	1.724	0.603
Eqty/Asset	7,091	0.064	0.086	0.119	0.101	0.056
Oth-Income/Asset	7,091	0.002	0.003	0.006	0.006	0.008
Ln(Bank Deposits)	7,091	0.000	0.000	0.000	0.136	0.622
Ln(Consumer Deposits)	7,091	2.797	3.597	4.627	3.758	1.354
Ln(# Depositors)	7,091	9.168	9.925	10.793	10.023	1.190
Dep Conc	7,091	0.127	0.186	0.268	0.213	0.129

The table reports the summary statistics, viz., the first quantile, the median, the third quantile, the mean and the standard deviation for key variables. These variables are defined in appendix B. The unit of observation is bank-year. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. All continuous variables are winsorized annually at 1%.

Table 3: Bank Characteristics by Quantiles of Deposit Concentration

Quant	Dep Conc	LN(Asset)	Eqty/Asset	NPL	Ln(Adv)	Ln(PSL)	Ln(Non-PSL)	OInc/Asset	NIM	RoAdv	CoF
1	0.062	1.095	0.148	0.225	1.534	1.366	0.530	0.008	0.031	0.177	0.057
2	0.102	1.374	0.113	0.147	2.105	1.907	0.847	0.006	0.032	0.183	0.063
3	0.127	1.486	0.104	0.119	2.325	2.097	1.064	0.006	0.032	0.180	0.061
4	0.150	1.599	0.098	0.115	2.580	2.317	1.312	0.006	0.031	0.178	0.062
5	0.173	1.724	0.093	0.108	2.836	2.554	1.539	0.005	0.032	0.181	0.065
6	0.200	1.818	0.091	0.089	3.059	2.758	1.751	0.005	0.031	0.176	0.064
7	0.230	1.893	0.088	0.087	3.227	2.887	1.985	0.005	0.031	0.180	0.067
8	0.267	1.950	0.094	0.081	3.332	2.974	2.111	0.006	0.031	0.179	0.065
9	0.322	2.028	0.087	0.063	3.494	3.096	2.353	0.006	0.031	0.178	0.064
10	0.460	2.242	0.089	0.049	3.922	3.441	2.923	0.006	0.029	0.176	0.067

The table reports the mean value of key bank characteristics by ten quantiles of deposit concentration. The characteristics include natural logarithm of total advances (LN(Adv)), natural logarithm of total priority sector loans (Ln(PSL)), natural logarithm of total non-priority sector loans (Ln(Non-PSL)), deposit concentration (Dep Conc), natural logarithm of book value of assets, equity to assets ratio (Eqty/Assets), other income to assets ratio (OInc/Asset), net interest margin (NIM), return on advances (RoAdv), cost of funds (CoF) and non-performing loan ratio (NPL). The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The variables are as defined as appendix B. All continuous variables are winsorized annually at 1%.

Table 4: Baseline Regression: Cooperative Bank Lending and Deposit Concentration

Dep Var: Ln(1+Advances)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Conc*Dual Election	-1.9221***	-1.1962***	-1.0812***	-1.0583***	-0.8704**	-0.1147**	-0.1145*	-0.1812***
	(0.2974)	(0.2877)	(0.2899)	(0.1913)	(0.3385)	(0.0481)	(0.0490)	(0.0213)
Dep Conc	4.9285***	4.7888***	5.0172***	4.9809***	4.1559***	0.8835***	0.8831***	0.8813***
	(0.4016)	(0.3389)	(0.3981)	(0.3907)	(0.3757)	(0.1155)	(0.1179)	(0.1527)
Dual Election	0.4639**	0.4684***	0.4172***					
	(0.1544)	(0.0787)	(0.0361)					
Constant	1.7934***	1.8040***	1.7583***	1.6676***	1.8291***	2.6392***	2.6393***	2.6600***
	(0.1315)	(0.0728)	(0.0877)	(0.0763)	(0.0774)	(0.0225)	(0.0229)	(0.0310)
State FE	No	Yes	Yes	No	No	No	No	No
Year FE	No	No	Yes	No	No	No	No	No
State-Year FE	No	No	No	Yes	Yes	Yes	Yes	No
District FE	No	No	No	No	Yes	No	Yes	No
Bank FE	No	No	No	No	No	Yes	Yes	Yes
District-Year FE	No	No	No	No	No	No	No	Yes
N	7,063	7,063	7,063	7,028	7,016	7,000	7,000	6,413
Adj. R^2	0.2194	0.3154	0.3279	0.3238	0.4527	0.9872	0.9866	0.9884

The table reports the results for the following regression where i indexes bank, j indexes district and t denotes time. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of total advances. α_j and θ_{jt} denotes the bank and district-year fixed effects respectively. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections.

$$y_{ijt} = \beta \text{Dual Election}_{j,(t+1)} * \text{Dep-Conc}_{it} + \beta_1 \text{Dep-Conc}_{it} + \alpha_i + \theta_{jt} + \epsilon_{ijt}$$

Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 5: Bank Level Time Varying Covariates

Dep Var: Ln(1+Advances)	(1)	(2)	(3)	(4)	(5)	(6)
Dep Conc*Dual Election	-0.1342**	-0.1358*	-0.1810***	-0.1839***	-0.1813***	-0.1293**
	(0.0408)	(0.0603)	(0.0255)	(0.0227)	(0.0213)	(0.0456)
Dep Conc	0.6172***	0.8263***	0.8783***	0.8790***	0.8813***	0.6145***
	(0.1215)	(0.1613)	(0.1540)	(0.1498)	(0.1532)	(0.1213)
Ln(Asset)	1.1988***					1.1734***
	(0.2058)					(0.2181)
Eqty/Asset		-1.4132**				-0.2020
		(0.3843)				(0.2195)
NIM			-0.2610			-0.4792*
			(0.2121)			(0.2348)
CoF				0.3087**		-0.0496
				(0.1135)		(0.1177)
Oth-Income/Asset					-0.2067	-0.1198
					(0.3420)	(0.2733)
Constant	0.7385*	2.9109***	2.6690***	2.6406***	2.6612***	0.8225*
	(0.3514)	(0.0455)	(0.0348)	(0.0376)	(0.0311)	(0.3847)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,404	5,404	6,413	6,413	6,413	5,404
Adj. R^2	0.9923	0.9904	0.9884	0.9884	0.9884	0.9923

The table reports the results for regression specification 1 while controlling for bank-specific time-varying covariates. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of total advances. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Time-varying covariates include log of assets, equity to assets ratio, net interest margin, cost of funds, other income to assets ratio, and non-performing loans ratio. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 6: Alternative Measurements of Bank Lending

Dep Var: $\frac{Advances_t}{Assets_{t-1}}$	(1)	(2)	(3)	(4)	(5)
Dep Conc*Dual Election	-0.0927***	-0.0242**	-0.0775**	-0.0486**	-0.0577**
	(0.0249)	(0.0080)	(0.0225)	(0.0141)	(0.0189)
Dep Conc	0.1287**	0.0643***	0.0888***	0.0175	0.0361
	(0.0399)	(0.0167)	(0.0135)	(0.0317)	(0.0278)
Ln(Asset)					0.0151
					(0.0383)
Eqty/Asset					-0.1598*
					(0.0717)
NIM					0.2250**
					(0.0809)
CoF					0.0451
					(0.0420)
Oth-Income/Asset					0.1427
					(0.0957)
Constant	0.4481***	0.4635***	0.4529***	0.4695***	0.4481***
	(0.0266)	(0.0026)	(0.0030)	(0.0063)	(0.0714)
State FE	No	Yes	No	No	No
Year FE	No	Yes	No	No	No
State-Year FE	No	No	Yes	No	No
District FE	No	No	Yes	No	No
Bank FE	No	No	No	Yes	Yes
District-Year FE	No	No	No	Yes	Yes
N	7,091	7,091	7,044	6,413	5,404
Adj. R^2	0.0212	0.3729	0.5144	0.8539	0.8669

The table reports the regression results for specification 1. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the total advances to assets ratio. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Time-varying covariates include log of assets, equity to assets ratio, net interest margin, cost of funds, other income to assets ratio, and non-performing loans ratio. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 7: Kitchen-Sink Analysis: Addressing Omitted variable Bias

Dep Var: Ln(1+Advances)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Conc*Dual Election	-0.1669**	-0.1664**	-0.1486*	-0.1717***	-0.1579**	-0.1592**	-0.1573**
	(0.0464)	(0.0577)	(0.0695)	(0.0416)	(0.0436)	(0.0443)	(0.0558)
Dep Conc	0.8533***	0.6258***	0.8332***	0.8544***	0.8524***	0.8518***	0.6218***
	(0.1708)	(0.1148)	(0.1596)	(0.1694)	(0.1696)	(0.1731)	(0.1144)
Ln(Asset)*Dual Election		0.0269*					0.0289*
		(0.0121)					(0.0130)
Ln(Asset)		1.1903***					1.1648***
		(0.2049)					(0.2161)
Eqty/Assets*Dual Election			-0.3796*				0.0328
			(0.1568)				(0.1163)
Eqty/Assets			-1.3635**				-0.2040
			(0.3853)				(0.2189)
NIM*Dual Election				-1.0000			-0.0305
				(1.1476)			(0.3500)
NIM				-0.5620			-0.4819
				(0.3630)			(0.3125)
CoF*Dual Election					-0.6095*		-0.0028
					(0.2653)		(0.4576)
CoF					0.4582**		-0.0516
					(0.1680)		(0.1139)
Oth-Income*Dual Election						1.1767	0.8310
						(1.7210)	(1.1728)
Oth-Income						-0.2700	-0.2009
						(0.1800)	(0.2137)
Constant	2.7618***	0.7526*	2.9050***	2.7791***	2.7320***	2.7635***	0.8379*
	(0.0374)	(0.3508)	(0.0454)	(0.0417)	(0.0445)	(0.0384)	(0.3838)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,404	5,404	5,404	5,404	5,404	5,404	5,404
Adj. R^2	0.9900	0.9923	0.9904	0.9901	0.9901	0.9900	0.9923

The table reports the regression results of cooperative bank lending on the double interaction term of deposit concentration and dual elections while controlling for the interaction terms of bank characteristics and dual election. Bank specific covariates include natural logarithm of book value of assets, bank equity to assets ratio, return on advances, net interest margin, cost of funds, other income to assets ratio, and non-performing loan ratio. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of total cooperative bank lending. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 8: Type of Cooperative Bank Lending and Deposit Concentration

	(1) PSL	(2) Non-PSL	(3) Agri	(4) SSI	(5) M&L	(6) Oth PSL
Dep Conc*Dual Election	-0.0982*	-0.1559**	-0.0300	-0.1514**	-0.1174	0.6916**
	(0.0416)	(0.0505)	(0.0204)	(0.0567)	(0.0656)	(0.2760)
Dep Conc	0.6416**	0.3585**	0.0659	0.2707	0.1887*	0.5687**
	(0.1760)	(0.1062)	(0.0747)	(0.1895)	(0.0851)	(0.2086)
Ln(Asset)	1.0257***	1.2227***	0.3401**	0.6317***	0.2818**	0.3596*
	(0.2603)	(0.1067)	(0.1310)	(0.1346)	(0.0979)	(0.1607)
Eqty/Asset	-0.2321	0.2296	0.1457	0.1550	0.3302*	-0.7455
	(0.3352)	(0.4266)	(0.0978)	(0.2072)	(0.1481)	(0.3859)
NIM	-0.3800	-0.0333	-0.0158	-0.0925	0.1395	1.0103
	(0.2443)	(0.3963)	(0.2434)	(0.3724)	(0.2974)	(0.6456)
CoF	-0.1045	0.1735	-0.0160	0.2700	-0.2350	-0.0683
	(0.2119)	(0.3914)	(0.2577)	(0.3438)	(0.1602)	(0.4703)
Oth-Income/Asset	0.5903	-0.9974	-0.3111	0.2519	1.2580	-0.6097
	(0.5323)	(0.6762)	(0.6148)	(0.7113)	(0.6654)	(0.9500)
Constant	0.7619	-0.4850**	-0.0374	-0.3786	-0.3743*	-0.3097
	(0.4547)	(0.1872)	(0.2309)	(0.2786)	(0.1578)	(0.2831)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,402	5,404	5,402	5,402	5,402	5,402
Adj. R^2	0.9795	0.9394	0.9103	0.9452	0.8513	0.7083

The table reports the regression results for specification 1. The dependent variable is the types of cooperative bank lending. Column 1 uses priority sector Credit (PSL), column 2 uses non-priority sector credit (Non-PSL), column 3 uses agricultural credit, column 4 uses credit to small scale industries, column 5 uses credit to medium and large scale industries and column 6 uses total other priority sector credit as the dependent variable. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Time-varying covariates include log of assets, equity to assets ratio, net interest margin, cost of funds, other income to assets ratio, and non-performing loans ratio. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 9: Non-Performing Loan Ratio, Dual elections and Deposit Concentration

Dep Var: NPL_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Conc*Dual Election	-0.0862**	-0.0569*	-0.0655***	-0.0667***	-0.0696***	-0.0673***	-0.0574*
	(0.0261)	(0.0260)	(0.0139)	(0.0108)	(0.0095)	(0.0080)	(0.0256)
Dep Conc	0.0380**	0.0272	0.0480	0.0502*	0.0494*	0.0504*	0.0254
	(0.0108)	(0.0267)	(0.0264)	(0.0230)	(0.0224)	(0.0223)	(0.0257)
Ln(Asset)		0.1516***					0.1417***
		(0.0230)					(0.0280)
Eqty/Asset			-0.1964***				-0.0571
			(0.0472)				(0.0489)
Oth-Income/Asset				-0.2112			-0.1176
				(0.2316)			(0.2315)
NIM					-0.1978**		-0.1779*
					(0.0749)		(0.0834)
CoF						-0.0508	0.0105
						(0.0846)	(0.0964)
Constant	0.0920***	-0.1764***	0.1024***	0.0833***	0.0883***	0.0852***	-0.1474**
	(0.0024)	(0.0415)	(0.0068)	(0.0052)	(0.0052)	(0.0029)	(0.0509)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,245	4,195	4,195	4,195	4,195	4,194	4,194
Adj. R^2	0.7966	0.8239	0.8207	0.8200	0.8203	0.8200	0.8240

The table reports the regression results of the cooperative bank NPL ratio on deposit concentration and dual elections. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the non-performing loan ratio. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 10: Jordà (2005) Linear Projection: Non-Performing Loan Ratio, Dual elections and Deposit Concentration

	(1) NPL_{t+1}	(2) NPL_{t+2}	(3) NPL_{t+3}	(4) NPL_{t+4}
Dep Conc*Dual Election	-0.0574*	-0.0702**	-0.0257	-0.0642*
	(0.0256)	(0.0214)	(0.0438)	(0.0155)
Dep Conc	0.0254	0.0725*	0.0523	0.0532
	(0.0257)	(0.0306)	(0.0604)	(0.0201)
Ln(Asset)	0.1417***	0.0970**	0.0350**	-0.0160**
	(0.0280)	(0.0263)	(0.0070)	(0.0025)
Eqty/Asset	-0.0571	-0.1475	-0.0444	-0.0839
	(0.0489)	(0.0712)	(0.1120)	(0.0789)
Oth-Income/Asset	-0.1176	0.0237	0.0649	0.6670
	(0.2315)	(0.1533)	(0.3998)	(0.8162)
NIM	-0.1779*	0.0242	0.0380	-0.2090
	(0.0834)	(0.1837)	(0.0661)	(0.0908)
CoF	0.0105	0.0842	0.0371	0.0744
	(0.0964)	(0.0823)	(0.0351)	(0.0375)
Constant	-0.1474**	-0.0938	-0.0002	0.0924**
	(0.0509)	(0.0542)	(0.0061)	(0.0116)
Bank FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
N	4,194	2,886	1,468	414
Adj. R^2	0.8240	0.8099	0.8444	0.9065

The table reports the regression results of the cooperative bank NPL ratio on deposit concentration and dual elections. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the non-performing loan (NPL) ratio. In column 1, 2, 3 and 4 we use NPL ratio one year, two years, three years and four years after respectively as in Jordà (2005). Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 11: Return on Advances, Deposit Concentration, and Dual Elections

	(1) $RoAdv_t$	(2) $RoAdv_{t+1}$	(3) NIM	(4) CoF
Dep Conc*Dual Election	0.0453*	0.0385*	0.0028	0.0086
	(0.0186)	(0.0162)	(0.0033)	(0.0070)
Dep Conc	-0.0088	0.0059	-0.0090**	0.0014
	(0.0112)	(0.0117)	(0.0035)	(0.0063)
Ln(Asset)	0.0591**	0.0509*	-0.0062	0.0429***
	(0.0212)	(0.0207)	(0.0046)	(0.0072)
Eqty/Asset	0.0762	0.1971	0.0023	-0.0176
	(0.0748)	(0.1067)	(0.0125)	(0.0157)
Oth-Inc/Asset	0.8629***	-0.3896*	0.0482	0.5154***
	(0.1955)	(0.1713)	(0.0670)	(0.0855)
Constant	0.0674	0.0724	0.0436***	-0.0113
	(0.0439)	(0.0427)	(0.0082)	(0.0123)
Bank FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
N	5,528	4,184	5,528	5,528
Adj. R^2	0.5898	0.5987	0.5045	0.4821

The table reports the regression results of the cooperative bank return on advances, net interest margin and cost of funds on deposit concentration and dual elections. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the return on advances in year t in column 1, the return of advances in year $t+1$ in column 2, net interest margin in column 3 and the cost of funds in column 4. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 12: Flighty Deposit, NPL and Deposit Concentration

Dep Var: Ln(Customer Deposits)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Conc*NPL	-0.9919*	-0.6929*	-1.1387**	-0.9864*	-1.0191**	-0.9828*	-0.7027*
	(0.4180)	(0.2953)	(0.4426)	(0.4122)	(0.3869)	(0.4225)	(0.2810)
NPL	0.0206	-0.0460	0.0681	0.0168	0.0088	0.0215	-0.0487
	(0.0836)	(0.0530)	(0.0855)	(0.0821)	(0.0742)	(0.0835)	(0.0491)
Dep Conc	0.4930**	-0.0389	0.4270*	0.4902**	0.4811**	0.4971**	-0.0402
	(0.1805)	(0.0728)	(0.1706)	(0.1794)	(0.1741)	(0.1796)	(0.0723)
Ln(Asset)		1.3690***					1.3670***
		(0.2573)					(0.2542)
Eqty/Asset			-1.3467***				-0.0872
			(0.2525)				(0.1970)
Oth-Income/Asset				-0.6243			0.1968
				(0.3487)			(0.3051)
NIM					-1.7546***		-1.4039***
					(0.4252)		(0.2781)
CoF						-0.1515	-0.3921*
						(0.1583)	(0.1856)
Constant	3.8150***	1.5555**	3.9621***	3.8196***	3.8749***	3.8238***	1.6375**
	(0.0359)	(0.4499)	(0.0312)	(0.0342)	(0.0305)	(0.0410)	(0.4565)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,780	4,780	4,780	4,780	4,780	4,780	4,780
Adj. R^2	0.9922	0.9944	0.9925	0.9922	0.9924	0.9922	0.9945

The table reports the regression results of customer deposits on NPL ratio at t and deposit concentration in $t-1$. The dependent variable is the natural logarithm of total customer deposits. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 13: Bank Failure and Deposit Concentration

Dep Var: $\mathbb{1}(Fail_{t+1})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Conc	-0.0713***	-0.1396*	-0.1078*	-0.1283**	-0.1445**	-0.1386*	-0.1400*	-0.1095*
	(0.0146)	(0.0506)	(0.0410)	(0.0430)	(0.0505)	(0.0507)	(0.0513)	(0.0397)
Ln(Asset)			-0.2853**					-0.2615**
			(0.0846)					(0.0673)
Eqty/Asset				0.5917				0.3887
				(0.2962)				(0.2499)
NIM					-0.6566			-0.8568
					(0.4391)			(0.4370)
CoF						-0.0463		-0.0088
						(0.1772)		(0.2441)
Oth-Income/Asset							0.1224	0.0769
							(0.1052)	(0.2771)
Constant	0.0311***	0.0408**	0.5421**	-0.0209	0.0627**	0.0437**	0.0402**	0.4883**
	(0.0062)	(0.0098)	(0.1532)	(0.0248)	(0.0210)	(0.0143)	(0.0095)	(0.1105)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4167	3691	3691	3691	3691	3691	3691	3691
Adj. R^2	0.0035	0.0325	0.0441	0.0385	0.0352	0.0321	0.0321	0.0497

The table reports the regression results of a linear probability model of cooperative bank failure as a function of deposit concentration. The dependent variable is a binary variable taking a value of 1 if the bank failed in next year or zero otherwise. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 14: What explains heterogeneity in Deposit Concentration?

Dep Var: Dep Conc	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Asset)	0.0959***							0.0925***	0.1764***
	(0.0115)							(0.0099)	(0.0472)
Eqty/Assets		-0.3951***						0.1123*	0.0943
		(0.0542)						(0.0551)	(0.0826)
RoAdv			-0.0206					0.0424	0.0685
			(0.0302)					(0.0386)	(0.0367)
NIM				-0.3189				-0.8353***	-0.3876**
				(0.1670)				(0.2039)	(0.1280)
CoF					0.4125			0.2081	-0.0426
					(0.2198)			(0.1421)	(0.0857)
Oth-Income/Asset						-0.4422		0.0395	0.0940
						(0.2552)		(0.3216)	(0.1278)
NPL							-0.2997***	-0.3025***	-0.0783**
							(0.0520)	(0.0459)	(0.0215)
Constant	0.0567***	0.2621***	0.2261***	0.2323***	0.1960***	0.2249***	0.2533***	0.0873***	-0.0824
	(0.0112)	(0.0134)	(0.0122)	(0.0155)	(0.0076)	(0.0121)	(0.0145)	(0.0136)	(0.0873)
Bank FE	No	No	No	No	No	No	No	No	Yes
District-Year FE	No	No	No	No	No	No	No	No	Yes
N	6,051	6,051	6,051	6,051	6,051	6,051	6,051	6,051	5,404
Adj. R^2	0.1982	0.0274	-0.0000	0.0012	0.0054	0.0004	0.0833	0.2730	0.8670

The table reports the regression results of cooperative bank deposit concentration on bank covariates: natural logarithm of book value of assets, bank equity to assets ratio, return on advances, net interest margin, cost of funds, other income to assets ratio, and non-performing loan ratio. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is deposit concentration. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Standard errors reported in parenthesis are double clustered by bank and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table 15: Bank Capitalization, Cooperative Bank Sector Lending and Deposit Concentration

Dep Var: Ln(1+Advances)	(1)	(2)	(3)	(4)	(5)	(6)
Dep Conc*Dual Election*Eqty/Assets	2.7330***	1.9486***	1.9522***	1.9005***	1.9504***	1.9059***
	(0.3136)	(0.2937)	(0.2939)	(0.2987)	(0.2867)	(0.2961)
Dep Conc*Eqty/Assets	-3.2116**	-2.4291***	-2.4274***	-2.3553**	-2.4129***	-2.3514**
	(0.9203)	(0.6157)	(0.6160)	(0.6454)	(0.6100)	(0.6399)
Eqty/Assets*Dual Election	-0.9362***	-0.3722**	-0.3729**	-0.3573**	-0.3746**	-0.3592**
	(0.1304)	(0.1037)	(0.1039)	(0.0987)	(0.1049)	(0.0993)
Dep Conc*Dual Election	-0.4500***	-0.3411***	-0.3419***	-0.3350***	-0.3407***	-0.3357***
	(0.0775)	(0.0457)	(0.0457)	(0.0430)	(0.0458)	(0.0432)
Dep Conc	1.1394***	0.8537***	0.8539***	0.8426***	0.8523***	0.8427***
	(0.1835)	(0.1378)	(0.1382)	(0.1385)	(0.1386)	(0.1392)
Eqty/Assets	-1.1187**	-0.0158	-0.0149	-0.0200	-0.0195	-0.0205
	(0.3432)	(0.2115)	(0.2109)	(0.2116)	(0.2155)	(0.2134)
Ln(Asset)		1.1578***	1.1580***	1.1563***	1.1626***	1.1582***
		(0.2194)	(0.2194)	(0.2195)	(0.2198)	(0.2216)
Oth-Income/Asset			-0.1621			-0.1207
			(0.2120)			(0.2502)
NIM				-0.4269*		-0.4088
				(0.2045)		(0.2298)
CoF					-0.1114	-0.0396
					(0.0888)	(0.1174)
Constant	2.8780***	0.8083*	0.8087*	0.8258*	0.8075*	0.8250*
	(0.0504)	(0.3828)	(0.3833)	(0.3883)	(0.3830)	(0.3899)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,404	5,404	5,404	5,404	5,404	5,404
Adj. R^2	0.9906	0.9924	0.9924	0.9924	0.9924	0.9924

The table reports the regression results of cooperative bank lending on the triple interaction term of deposit concentration, bank equity to assets ratio and dual elections. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of total cooperative bank lending. Eqty/Assets is the ratio of the book value of equity to the book value of total assets. Deposit Concentration is computed as the ratio of total consumer deposits to the number of consumer depositors. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Appendix A Proof of Proposition 2.1

Proof.

Deviations of the small depositor First consider possible deviations of the small depositor, taking as given the equilibrium strategies of the big depositor and the banks.

- Suppose the small depositor chooses the bad bank.
  - If the small depositor monitors the bad bank, then according to the bad bank's equilibrium strategy, the bad bank works. The small depositor gets $\gamma w_S + \rho(1-\gamma) w_S - c$ if he runs at $t = 1$, and gets $(p + \Delta_p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$ otherwise. Assumption 2 implies that

    $$\gamma w_S + \rho(1-\gamma) w_S - c \quad < \quad (p + \Delta_p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$$

    So the small depositor should not run conditional on monitoring the bad bank, and he receives payoff $(p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$ in this case.
  - If the small depositor does not monitor the bad bank, then according to the bad bank's equilibrium strategy, the bad bank shirks. The small depositor gets $\gamma w_S + \rho(1-\gamma) w_S$ if he runs at $t = 1$, and gets $p w_S + (1-p) \rho w_S + b_S$ otherwise. Assumption 1 and 2 imply that

    $$p w_S + (1-p) \rho w_S + b_S \quad > \quad \gamma w_S + \rho(1-\gamma) w_S$$

    So the small depositor should not run conditional on not monitoring the bad bank, and he receives payoff $p w_S + (1-p) \rho w_S + b_S$ in this case.

  Assumption 2 implies that

  $$p w_S + (1-p) \rho w_S + b_S \quad > \quad (p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$$

  Hence, if the small depositor chooses the bad bank, he should not monitor the bad bank and should not run at $t = 1$. He gets payoff $p w_S + (1-p) \rho w_S + b_S$ in this case.

- Suppose the small depositor chooses the good bank.
  - If the small depositor monitors the good bank, then according to the good bank's equilibrium strategy, the good bank works. The small depositor gets $\gamma(w_B + w_S) + \rho(w_S - \gamma(w_B + w_S)) - c$ if he runs at $t = 1$, and gets $(p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$ otherwise. Assumption 2 implies that

    $$\gamma(w_B + w_S) + \rho(w_S - \gamma(w_B + w_S)) - c \quad < \quad (p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$$

    So the small depositor should not run conditional on monitoring the good bank, and he receives payoff $(p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$ in this case.
  - If the small depositor does not monitor the good bank, then according to the good bank's equilibrium strategy, the good bank shirks. The small depositor gets ρw_S if he runs at $t = 1$, and gets ρw_S otherwise.

    So the small depositor is indifferent between run/no run conditional on not monitoring the good bank, and he receives payoff ρw_S in this case.

  Assumption 2 implies that

  $$(p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c \quad > \quad \rho w_S$$

  Hence, if the small depositor chooses the good bank he should monitor the bank and should not run at $t = 1$. He gets payoff $(p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$ in this case.

Now we can compare the maximum payoff to the small depositor, when he chooses the good bank versus when he chooses the bad bank. Assumption 2 implies that

$$p w_S + (1 - p) \rho w_S + b_S \quad > \quad (p + \Delta p) w_S + (1 - p - \Delta_p) \rho w_S + b_S - c$$

So the small depositor will not deviate from his equilibrium strategy, which is to choose the bad bank, not monitor the bad bank and not run.

Deviations of the big depositor Then we consider possible deviations of the big depositor, taking as given the equilibrium strategies of the small depositor and the banks.

- Suppose the big depositor chooses the good bank.
  - If the big depositor monitors the good bank, then according to the good bank's equilibrium strategy, the good bank works. The big depositor gets $\gamma w_B + \rho(1-\gamma) w_B - c$ if he runs at $t = 1$, and gets $(p + \Delta p) w_B + (1 - p - \Delta_p) \rho w_B + b_B - c$ otherwise. Assumption 4 implies that

    $$\gamma w_B + \rho(1-\gamma) w_B - c \quad < \quad (p+\Delta p) w_B + (1-p-\Delta_p) \rho w_B + b_B - c$$

    So the big depositor should not run conditional on monitoring the good bank, and he receives payoff $(p + \Delta p) w_B + (1 - p - \Delta_p) \rho w_B + b_B - c$ in this case.
  - If the big depositor does not monitor the good bank, then according to the good bank's equilibrium strategy, the good bank shirks. The big depositor gets $\gamma w_B + \rho(1-\gamma) w_B$ if he runs at $t = 1$, and gets $p w_B + (1-p) \rho w_B + b_B$ otherwise. Assumption 4 implies that

    $$p w_B + (1-p) \rho w_B + b_B \quad < \quad \gamma w_B + \rho(1-\gamma) w_B$$

    So the big depositor should run conditional on not monitoring the good bank, and he receives payoff $\gamma w_B + \rho(1-\gamma) w_B$ in this case.

  Assumption 4 implies that

  $$(p+\Delta p) w_B + (1-p-\Delta_p) \rho w_B + b_B - c \quad > \quad \gamma w_B + \rho(1-\gamma) w_B$$

  Hence, if the big depositor chooses the good bank, he should monitor the good bank and should not run at $t = 1$. He gets payoff $(p + \Delta p) w_B + (1 - p - \Delta_p) \rho w_B + b_B - c$ in this case.

- Suppose the big depositor chooses the bad bank.

– If the big depositor monitors the bad bank, then according to the bad bank's equilibrium strategy, the bad bank shirks. The big depositor gets $\gamma(w_B + w_S) + \rho(w_B - \gamma(w_B + w_S)) - c$ if he runs at $t = 1$, and gets $pw_B + (1-p)\rho w_B + b_B - c$ otherwise. Assumption 4 implies that

$$\gamma(w_B + w_S) + \rho(w_B - \gamma(w_B + w_S)) - c \quad > \quad pw_B + (1-p)\rho w_B + b_B - c$$

So the big depositor should run conditional on monitoring the bad bank, and he receives payoff $\gamma(w_B + w_S) + \rho(w_B - \gamma(w_B + w_S)) - c$ in this case.

– If the big depositor does not monitor the bad bank, then according to the bad bank's equilibrium strategy, the bad bank shirks. The big depositor gets $\gamma w_B + \rho(1-\gamma) w_B$ if he runs at $t = 1$, and gets ρw_B otherwise. Since $\rho w_B < \gamma w_B + \rho(1-\gamma) w_B$, the big depositor should run conditional on not monitoring the bad bank, and he receives payoff $\gamma w_B + \rho(1-\gamma) w_B$ in this case.

Assumption 2 implies that

$$\gamma w_B + \rho(1-\gamma) w_B \quad > \quad \gamma(w_B + w_S) + \rho(w_B - \gamma(w_B + w_S)) - c$$

Hence, if the big depositor chooses the bad bank he should not monitor the bank and should run at $t = 1$. He gets payoff $\gamma w_B + \rho(1-\gamma) w_B$ in this case.

Now we can compare the maximum payoff to the big depositor, when he chooses the good bank versus when he chooses the bad bank. Assumption 4 implies that

$$(p + \Delta p) w_B + (1 - p - \Delta_p) \rho w_B + b_B - c \quad > \quad \gamma w_B + \rho(1-\gamma) w_B$$

So the big depositor will not deviate from his equilibrium strategy, which is to choose the good bank, monitor the good bank and not run.

Deviations of the good bank Now we consider possible deviations of the good bank, taking as given the equilibrium strategies of the depositors and the bad bank. Since in equilibrium only the big depositor chooses the good bank, we only need to consider whether the good bank has an incentive to shirk. Specifically, if the good bank shirks, the big depositor runs, so the good bank receives 0, which is less than his payoff from working $(p + \Delta p)(R - 1) w_B + (1 - p - \Delta p) k_G w_B$. Hence, the good bank will not deviate from his equilibrium strategy.

Deviations of the bad bank Finally, we consider possible deviations of the bad bank, taking as given the equilibrium strategies of the depositors and the good bank. Since in equilibrium only the small depositor chooses the bad bank, we only need to consider whether the bad bank has an incentive to work. Specifically, if the bad bank works, the small depositor does not run, so the bad bank receives $(p + \Delta p)(R - 1) w_S + (1 - p - \Delta p) k_B w_S$, which is less than his payoff from shirking $p(R - 1) w_S + (1 - p) k_B w_S$ under assumption 3. Hence, the bad bank will not deviate from his equilibrium strategy. $\square$

Appendix B Definition of Variables

The definition of key variables employed in the study is as follows:

- **Ln(1+Adv)**: Natural logarithm of one plus total advances. Advances for cooperative banks include loan facilities issued by the bank

- **Ln(1+PSL)**: Natural logarithm of one plus loans extended to the priority sector

- **Ln(1+Non-PSL)**: Natural logarithm of one plus loans extended to the non-priority sector

- **Ln(1+Agriculture)**: Natural logarithm of one plus loans extended to agriculture within the priority sector

- **Ln(1+SSI)**: Natural logarithm of one plus loans extended to small scale industries within the priority sector

- **Ln(1+M&L)**: Natural logarithm of one plus loans extended to medium and large scale industries within the priority sector

- **Ln(1+Other PSL)**: Natural logarithm of one plus loans extended to other small categories within the priority sector

- **NIM**: Net Interest Margin. NIM is calculated as the ratio of difference between interest income and interest expense to advances.

- **CoF**: Cost of Funds. Cost of funds is computed as the ratio of interest expense to borrowed funds. These funds include deposits and loans taken from other banks, government, private individuals and the central bank.

- **Ln(Assets)**: Natural logarithm of total book value of asets.

- **Eqty/Assets**: Ratio of book value of total equity to the book value of total assets.

- **Oth-Income/Assets**: Ratio of other income to the book value of assets.

- **Ln(Bank deposits)**: Natural logarithm of inter bank deposits held in a bank.

- **Ln(Customer deposits)**: Natural logarithm of customer deposits held in a bank. This does not include the deposits of founder members of the bank.
- **Ln(# Depositors)**: Natural logarithm of total number of customer depositors. This does not include founding depositors.
- **Dep Conc**: Deposit Concentration is defined as the ratio of total customer deposits (in ten thousand) to number of depositors.
- **Op Exp**: Operating Expenses is defined as non-interest expense incurred y banks.
- **g(NDDP)**: Growth rate of net district domestic product .
- **g(Unreg NDP)**: Growth rate of state level net domestic product attributed to unregulated manufacturing sector.

Appendix C Electoral Cycle and Cooperative Bank Lending

Appendix C provides a verification to our conjecture that periods of elections are marked by electorally motivated lending by cooperative banks. The empirical specification we run to test our conjecture is as follows:

$$y_{it} = \beta \text{Dual-Election}_{i,(t+1)} + \alpha_i + \gamma_j + \theta_t + \epsilon_{ijt} \tag{C.1}$$

The dependent variable in equation C.1 is the natural logarithm of one plus credit. α_i, γ_j and θ_t denotes the bank, district and year fixed effects respectively. The coefficient of interest is the parameter associated with Dual-Election$_{i,(t+1)}$. Consistent with our conjecture our null hypothesis is that $\beta > 0$. Table C.1 reports the baseline results for the electoral lending among cooperative banks between 2006 and 2013. As hypothesized the coefficient associated with Dual-Election$_{i,(t+1)}$ is positive and significant at 1% level. The model adjusted R^2 increases from 0.11 to 0.98 between column 1 to column 6 but our coefficient of interest is relatively stable. Periods of dual elections are marked by 15%-20% growth in total credit extended by cooperative banks. The point estimate in column 3 is a within bank estimator and compares the growth in credit for a given bank between periods of dual election and non dual election while controlling for state specific business cycles. The standard errors are double clustered by state and year.

Table C.2 shows the results for different credit types. Column 1 uses total credit, column 2 uses priority sector Credit (PSL), column 3 uses non-priority sector credit (Non-PSL), column 4 uses agricultural credit, column 5 uses credit to small scale industries, column 6 uses credit to medium and large scale industries and column 7 uses total other priority sector credit as dependent variable. The point estimate for total advances, priority sector advances and non-priority sector advances is positive. However, the point estimate for agricultural lending is negative and in contrast to the findings of Cole (2009). We attribute this difference to two reasons. First, the sample used in Cole (2009) is that of state-owned banks across the country, whereas our sample is restricted to only urban branches of cooperative banks. Second, unlike state-owned banks, cooperative banks do not have a mandate to lend to agriculture, rather they have a mandate to lend to small scale industries.

Thus far, we have established that the temporal variation in bank credit is highly correlated with the dual election cycle. These results are based on the volume of credit; it does not identify whether these results are driven by changes in the demand for or the supply of loans. It is possible that the increase in public spending via an increase in money supply during periods of election can trigger a positive aggregate demand shock. This, in turn, can induce firms to increase borrowing to meet additional demand. To investigate this empirically, we focus on the price of credit. If the increase in lending by banks is the result of increased demand, then it is likely to be accompanied by an increase in price. Column 1 of table C.3 reports the results of dual election on net interest margin (NIM). Contrary to the demand based explanation of the rise in the volume of credit, NIM decreases. In column 2 we show that this decline in NIM is not driven by a decline in cost of funds. Moreover, a demand based explanation would require return on advances to go up. However, the results reported in column 3 show that return on advances (RoAdv) are negatively associated with dual election. Column 4 rules out an alternative explanation of decline in RoAdv via an increase in operating expenses.

Next, we examine if the increased lending during years of twin elections exerts a perceptible impact on real economic activity. To test this, we use the growth rate in net domestic district product (NDDP) and the growth rate in net domestic product from unregistered manufacturing (UnregGDP) at state level. Table C.4 shows the result for growth rate in NDDP (g(NDDP)) upto $t+3$ years following the dual elections. The level impact of dual election is ambiguous. It is negative and insignificant in column 1, positive and significant in column 3 and 5 and turns insignificant in column 7. We add the interaction term of dual election and share of advances by cooperative banks in that district. The interaction term is negative and significant in column 2, 4 and 8. The overall impact of lending by cooperative banks during dual elections appears to be negatively related to g(NDDP) in column 2 and column 8. Next, in table C.5 we evaluate the impact of cooperative bank lending to small scale industry on g(UnregGDP). While the overall contemporaneous impact is positive, it turns negative after one period, again turning positive for period $t + 2$ and $t + 3$. Overall, the evidence on the real effects of electoral lending by cooperative banks on real activity is inconclusive at best.

Finally, we conduct a placebo test to rule out any mechanical relationship between bank lending and electoral cycle. We do 3,500 Monte Carlo simulations and generate a new Dual Election variable for each state in every simulation by assigning the probability that each state-year faces a dual election to be 0.2. We call this new dual election year as placebo dual election year. For each simulation we estimate β as in equation C.1. Figure C.1 shows the kernel density plot of the point estimates of β from 3,500 simulations. We are able to reject the null of zero point estimate about 5.1% time under a one sided test and 10.9% times under a two-sided test. The maximum value of β from simulations is 0.02 which is almost ten times smaller than the point estimate presented in table C.1.

Table C.1: Electoral Lending Cycle and Cooperative Bank Lending

Dep Var: Ln(1+Advances)	(1)	(2)	(3)	(4)	(5)	(6)
Dual Election	0.2215**	0.1475***	0.2010***	0.2076***	0.1656***	0.1748***
	(0.0740)	(0.0389)	(0.0099)	(0.0131)	(0.0103)	(0.0148)
Big Bank				0.1765***		0.1730***
				(0.0335)		(0.0336)
High Cap					-0.0581***	-0.0536***
					(0.0108)	(0.0113)
Constant	2.8202***	2.8302***	2.9382***	2.8464***	2.9774***	2.8843***
	(0.0076)	(0.0034)	(0.0013)	(0.0139)	(0.0051)	(0.0141)
State FE	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	No	No
Bank FE	No	No	Yes	Yes	Yes	Yes
N	7,063	7,054	7,035	7,035	7,035	7,035
Adj. R^2	0.1154	0.3564	0.9861	0.9866	0.9862	0.9867

The table reports the regression results of natural logarithm of total advances on the dual election binary variable. Big bank takes a value of 1 if the natural logarithm of total book value of assets is greater than the median value of book value of assets of all cooperative banks in that state year. High Cap takes a value of 1 if the equity to assets ratio is greater than the median value of equity to assets ratio of all cooperative banks in that state year. Dual Election takes a value of 1 during years of simultaneous state and federal elections. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table C.2: Electoral Lending Cycle and Cooperative Bank Lending: Type of Advances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Adv)	Ln(PSL)	Ln(Non-PSL)	Ln(Agri)	Ln(SSI)	Ln(M&L)	Ln(Oth PSL)
Dual-Election	0.2010***	0.0962***	0.2685***	-0.0652***	0.0189	-0.2993***	1.1499***
	(0.0099)	(0.0126)	(0.0211)	(0.0165)	(0.0107)	(0.0162)	(0.0314)
Constant	2.9382***	2.6453***	1.7519***	0.5962***	0.7407***	0.2578***	0.2147***
	(0.0013)	(0.0044)	(0.0041)	(0.0061)	(0.0027)	(0.0084)	(0.0104)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,035	7,031	7,035	7,031	7,031	7,031	7,031
Adj. R^2	0.9861	0.9725	0.9299	0.9075	0.9431	0.8762	0.7103

The table reports the regression results of natural logarithm of different kind of advances on the dual election binary variable. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Column 1 uses total credit, column 2 uses priority sector Credit (PSL), column 3 uses non-priority sector credit (Non-PSL), column 4 uses agricultural credit, column 5 uses credit to small scale industries, column 6 uses credit to medium and large scale industries and column 7 uses total other priority sector credit as dependent variable. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table C.3: Electoral Lending Cycle and Loan Pricing

	(1)	(2)	(3)	(4)
	NIM	CoF	RoAdv	Op Exp
Dual-Election	-0.0023***	0.0069***	-0.0052**	-0.0043***
	(0.0006)	(0.0007)	(0.0019)	(0.0004)
Constant	0.0320***	0.0644***	0.1803***	0.0144***
	(0.0002)	(0.0002)	(0.0005)	(0.0001)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7,063	7,063	7,063	7,063
Adj. R^2	0.4523	0.4217	0.5110	0.3063

The table reports the regression results of loan pricing bank characteristics on the dual election binary variable. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Column 1 uses net interest margin (NIM), column 2 uses cost of funds (CoF), column 3 uses return on advances (RoAdv) and column 4 uses operating expenses (Op Exp). Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table C.4: Electoral Cycle and district level NDP growth rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$g(NDDP)_t$		$g(NDDP)_{t+1}$		$g(NDDP)_{t+2}$		$g(NDDP)_{t+3}$	
Dual-Election	-0.0025	-0.0022	0.0169**	0.0172**	0.0209***	0.0212***	0.0034	0.0041
	(0.0066)	(0.0067)	(0.0054)	(0.0055)	(0.0045)	(0.0046)	(0.0061)	(0.0063)
Sh. Adv*Dual-Election		-0.0742**		-0.0362*		-0.0351		-0.0611*
		(0.0297)		(0.0169)		(0.0218)		(0.0268)
Sh. Adv		0.0548**		0.0354**		0.0237		0.0527**
		(0.0157)		(0.0119)		(0.0136)		(0.0168)
Constant	0.0705***	0.0702***	0.0678***	0.0676***	0.0645***	0.0644***	0.0625***	0.0621***
	(0.0058)	(0.0058)	(0.0054)	(0.0054)	(0.0045)	(0.0046)	(0.0058)	(0.0059)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1541	1541	1210	1210	933	933	662	662
Adj. R^2	0.0144	0.0234	0.1377	0.1413	0.2912	0.2930	0.0058	0.0344

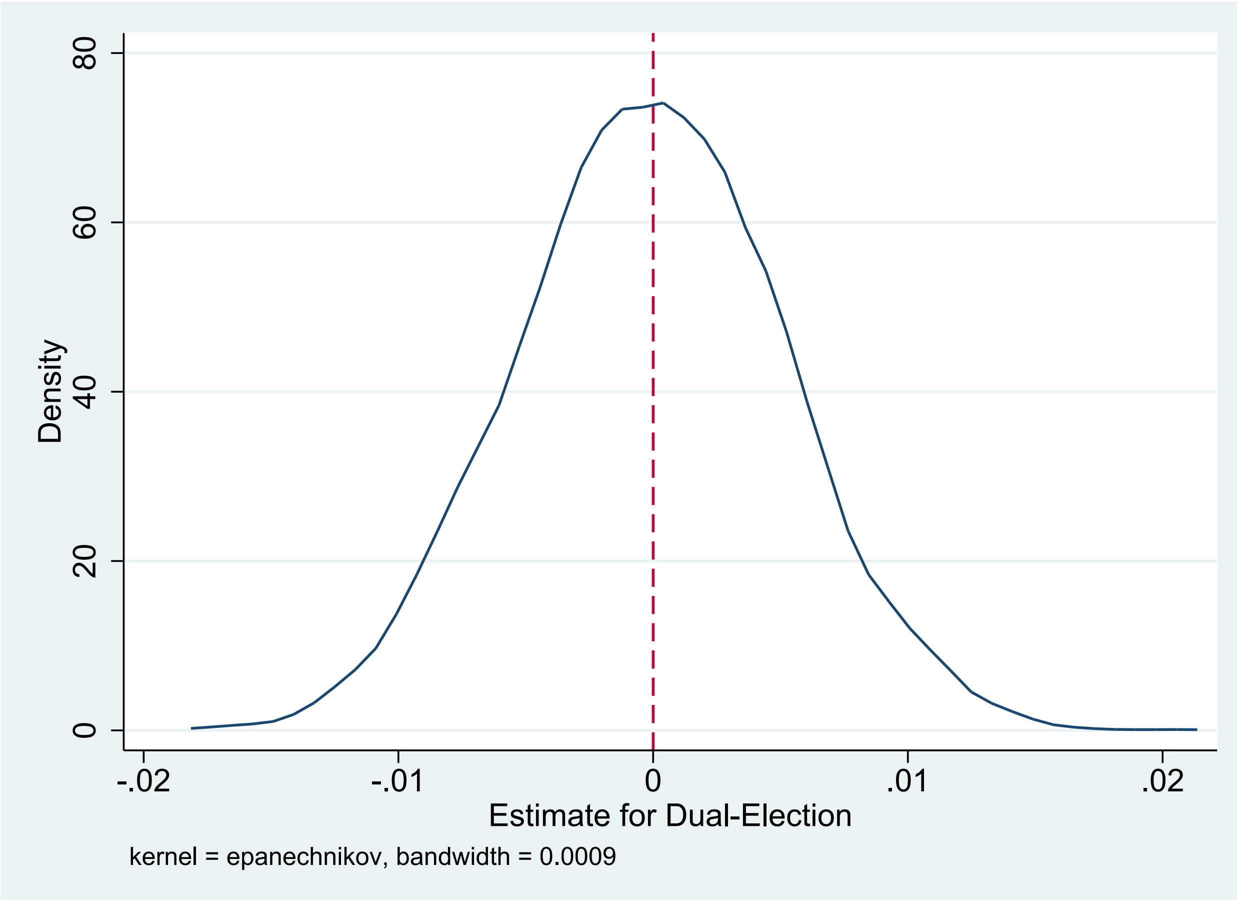
The table reports the regression results of growth rate of net domestic district product (NDDP) on the dual election binary variable. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Column 1 and column 2 uses growth rate of net domestic district product (NDDP) in period t, column 3 and column 4 uses growth rate of net domestic district product (NDDP) in period $t+1$, column 5 and column 6 uses growth rate of net domestic district product (NDDP) in period $t+2$, and column 7 and column 8 uses growth rate of net domestic district product (NDDP) in period $t+3$. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Table C.5: Electoral Cycle and Unregistered Manufacturing Sector NDP growth rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$g(UnregNDP)_t$		$g(UnregNDP)_{t+1}$		$g(UnregNDP)_{t+2}$		$g(UnregNDP)_{t+3}$	
Dual-Election	0.0143	0.0074	-0.0141	-0.0071	-0.0272	-0.0331	0.0320**	0.0244**
	(0.0148)	(0.0147)	(0.0208)	(0.0222)	(0.0222)	(0.0232)	(0.0117)	(0.0109)
Dual-Election*Sh. SSI		0.1408***		-0.0943**		0.0811***		0.1059***
		(0.0265)		(0.0375)		(0.0272)		(0.0153)
Sh. SSI		0.2035		0.1844		0.2311		0.2806***
		(0.4515)		(0.6963)		(0.4816)		(0.0725)
Constant	0.0480***	0.0390*	0.0485***	0.0405	0.0423***	0.0320	0.0298***	0.0169***
	(0.0017)	(0.0203)	(0.0013)	(0.0298)	(0.0017)	(0.0220)	(0.0011)	(0.0034)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	178	178	162	162	134	134	109	109
Adj. R^2	-0.0745	-0.0730	-0.0914	-0.1013	0.0580	0.0488	0.3957	0.3952

The table reports the regression results of growth rate of state level NDP coming from unregistered manufacturing sector on the dual election binary variable. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. Column 1 and column 2 uses growth rate of state level GDP coming from unregistered manufacturing sector in period t, column 3 and column 4 uses growth rate of state level GDP coming from unregistered manufacturing sector in period $t+1$, column 5 and column 6 uses growth rate of state level GDP coming from unregistered manufacturing sector in period $t+2$, and column 7 and column 8 uses growth rate of state level GDP coming from unregistered manufacturing sector in period $t+3$. Dual Election takes a value of 1 during years of simultaneous state and federal elections. Sh. SSI gives the share of lending going to small scale industries in that state year. It is calculated as the ratio of SSI lending in that state-year to the total SSI lending in that year. Standard errors reported in parenthesis are double clustered by state. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%.

Figure C.1: Placebo Test



Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	St Dev
-0.017	-0.012	-0.009	-0.004	0.000	0.003	0.008	0.012	0.020	0.000	0.005

The figure plots the kernel density of the point estimates of the Dual Election obtained from the 3,500 Monte Carlo simulations. We generate a new Dual Election variable for each state in every simulation by assigning the probability that each state-year faces a dual election to be 0.2. We call this new dual election year as placebo dual election year. The sample comprises of 1,464 urban cooperative banks spread across 276 districts in 27 states between 2006 and 2013. The dependent variable is the natural logarithm of one plus credit. α_i and θ_{st} denotes the bank and state-year fixed effects.

$$y_{it} = \beta \text{Placebo Dual Election}_{j,(t+1)} + \alpha_i + \theta_t + \epsilon_{ijt}$$

Standard errors reported in parenthesis are double clustered by state and year. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. All variables are winsorized annually at 1%. The table underneath the figure gives the numbers associated with the distribution of the estimates plotted in figure C.1. We are able to reject the null of zero point estimate about 5.1% time under a one sided test and 10.9% times under a two-sided test.

Appendix D Testing for Omitted Variable Bias, Oster (2019)

In this section we provide details of the Oster (2019) test and calculation of the identified set and the relative strength of unobservables to observable for zero to be included in the identified set. Oster (2019) is a modified version of Altonji, Elder and Taber (2005). Let the true model be given by:

$$Y = \beta X + \gamma W_1 + \delta W_2 + \epsilon \tag{D.1}$$

In the above model we are interested in capturing the effect of X on Y. So the parameter of interest is β. W_1 and W_2 denote vector of observable and unobservable covariates. Given that we cannot control for W_2 the estimate of β from the eregression of X on Y while controlling for W_1 will be plagued by omitted variable bias if $\mathbb{E}(X, W_2) \neq 0$. Oster (2019) suggestes estimating the following two regressions:

- Model 1: $Y = \bar{\beta} X + \bar{\varepsilon}$, $\bar{R}^2$.
- Model 2: $Y = \tilde{\beta} X + \tilde{\psi} W_1 + \tilde{\varepsilon}$, $\tilde{R}^2$.

$\bar{R}^2$ and $\tilde{R}^2$ denotes the model R^2 for model 1 and 2 respectively. Using the parameters in model 1 and 2 and the R^2 for model 1, 2 and the true model we can estimate a new parameter β^*. Under the assumption that the relative strength of observable to un-observable is 1 β^* is given by the following equation and $\beta^* \xrightarrow{p} \beta$.

$$\beta^* = \tilde{\beta} - \left(\bar{\beta} - \tilde{\beta}\right) \frac{R^2_{max} - \tilde{R}^2}{\tilde{R}^2 - \bar{R}^2}$$

Here, R^2_{max} is the maximum R^2 that the true model can have. We have $R_{max} \equiv \min\left\{\theta \tilde{R}^2, 1\right\}$ with $\theta > 1$. Oster (2019) suggests a value of 2.2 for the value of θ. Then we define the identified set $\Omega = [\beta^*, \tilde{\beta}]$, if $0 \notin \Omega$, we reject the null that effect of X on Y is driven by omitted variables. The identified set is created assuming the relative strength of un observales to observables is 1 ($\lambda = 1$). Alternatively we can define λ (given by the following equation) as the value required such that zero is included in Ω.

$$\lambda = \frac{\tilde{\beta}\left(\tilde{R}^2 - \bar{R}^2\right)}{\left(\bar{\beta} - \tilde{\beta}\right)\left(R^2_{max} - \tilde{R}^2\right)}$$

We estimate our baseline specification with and without the bank fixed effects. The table D.1 shows the point estimate and regression R^2 for the baseline specification with and without bank fixed effects. using the information from table D.1 and substituting $R^2_{max} = 1$ we estimate the set Ω and the parameter λ as follows:

$$\Omega = [-0.1812, -0.1664]$$

$$\lambda \approx 12.2$$

The set Ω does not include 0 so we can reject the null that our point estimate of interest is contaminated by omitted variable bias. Alternatively, the value of λ required to have zero inside Ω is extremely high given the model R^2 in column 2 of table D.1.

Table D.1: Testing for Omitted variable Bias

Dep Var: Ln(1+Advances)	(1)	(2)
Dep Conc*Dual Election	-1.2130***	-0.1812***
	(0.3059)	(0.0213)
Dep Conc	4.3176***	0.8813***
	(0.4055)	(0.1527)
Constant	1.8369***	2.6600***
	(0.0842)	(0.0310)
District-Year FE	Yes	Yes
Bank FE	No	Yes
N	6,413	6,413
R^2	0.4644	0.9924