Does facetime with the boss matter? Soft information communication and organizational performance

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Abstract

Can better communication with the boss (she) improve the performance of the employees (he), even if he has authority for making decisions? The term boss, in our paper, refers to the person who decides the remuneration of the employee based on his performance. An employee's performance depends not only on his effort but also on unpredictable factors beyond his control, which may be soft information. Communicating this soft information through face-to-face interaction would allow the employee to explain why he may have performed poorly (or well). Using the informativeness principle, the boss can offer more efficient contracts *ex ante* which share more risk and elicit higher level of effort by the employees. Using granular within bank data, we exploit exogenous change in the ability of bank managers to communicate with their boss and show that better communication improves their productivity. The results in the paper suggest that there may be an alternative complementary explanation (compared to Stein (2002)) for why small banks are more efficient at lending to small businesses.

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1 Introduction

Frictions in information communication across hierarchies in an organization may impede decision-making. While improvement in information communication technology can overcome such frictions (Bloom et al., 2014), hard-to-codify soft information may be impervious to such technological change. These frictions, then, affect how organizations design themselves and allocate control within the organization. For example, in order to utilize such information, some firms delegate more decision-making power to managers (Aghion and Tirole, 1997; Stein, 2002; Berger et al., 2005; Garicano, 2000; Bloom et al., 2013). However, can improvement in soft information communication improve performance of employees even if the authority to make decisions remains with the employee?

In this paper, we provide evidence that better communication through face-to-face interactions with the boss (she) improves the performance of the employees (he), in our case the bank managers, even though authority lies with the bank manager. Why should better communication affect employee decision making and improve performance at all even when he has all the authority over making decisions? An employee's performance, keeping his ability constant, depends not only on his effort but also on luck, i.e., unpredictable exogenous shocks which are beyond his control. For example, the size and performance of a loan officer's portfolio could be affected by unexpected local demand downturns and productivity shocks that the borrowers may face respectively. If these unexpected shocks are soft information, then a loan officer needs face-to-face communication with his boss to explain why he may have performed poorly (or well). The boss, who is responsible for remuneration setting, can thus reward him for his performance more accurately by taking into account these shocks which may have affected his performance. So according to the informativeness principle (Holmström, 1979), improved communication would allow her to offer more efficient contracts *ex ante* which share more risk and elicit higher level of effort by the employees.

While the importance of frictions in information production and communication within an organization is well understood theoretically (Aghion and Tirole, 1997; Stein, 2002; Garicano and Rossi-hansberg, 2005; Bolton and Dewatripont, 1994), the empirical literature is relatively scant because of multiple reasons. First, within-firm data on changes in organization and outcome variables are scarce. Second, even if data is available, change in an employee's ability to communicate with his boss may not be random. Finally, an employee's ability to communicate with the boss and his authority over decisions may be correlated. For example, an employee may be able to communicate soft information only at some hierarchical level, and not others. This makes it difficult to study the impact on productivity and disentangle the effect of improved communication from change in authority or roles.

We answer our questions by studying the Lead Bank scheme in India, where the institutional setting allows us to study exogenous changes in ability of employees to communicate with the boss. This scheme was started in 1969 to improve credit access to priority sectors such as agricultural sector, small businesses and marginalized sections of society who need smaller loans.[1] Under this scheme, one commercial public sector bank in each district is assigned the role to promote credit supply to these sectors in that district.[2] This bank is called the Lead Bank for that district. In order to assess credit delivery to priority sectors, the Reserve Bank of India appointed another commercial public sector bank at the state level. These banks are called the Convener Banks. Thus, there are some districts where the same banks act as both the Lead Banks and the Convener Banks. We refer to these Lead Banks as *aligned*.

The Convener Banks hold a meeting every quarter to review the performance of the Lead Banks. These meetings are headed by the CEO or the managing director of the Convener bank. When the Lead Banks are aligned, the employee of the Lead Bank has the opportunity to explain his performance to the CEO of his own bank every quarter, who directly controls performance-based rewards of the employee. These employees can expect to be rewarded appropriately taking into account the unexpected shocks that may be affecting his performance. Conversely, for Lead Banks which are not aligned, soft information exchange with the CEO of a different bank holds much lesser value in terms of reward determination.

We exploit exogenous change in *alignment* to study how variation in communication with his boss affects the performance of the employees. Alignment of a Lead Bank changes mainly due to splitting of old states in which case the newly formed states get new convener banks. These factors are unlikely to be correlated with the district-level performance of the banks. We have data on district level lending in different sectors, lending rate, non performing assets and number of loan officers for each bank operating in a district. Our data is rich enough to use specifications which include district-time fixed effects to control for district level time varying characteristics such as local demand, bank-time fixed effects to control for bank-level time varying characteristics, and bank-district fixed effect to control for, among other factors, the appointment of a particular bank as Lead Bank in that district.

We examine the impact of alignment for rural and urban areas separately. Our hypothesis is that there should be an increase in only rural credit where most of the credit disbursed comes under the category of priority sector loans. Contrarily, there should be minimal

[1] We discuss priority sector lending in greater detail in section 2.

[2] In India, public sector bank are mostly owned by the government, although these banks could be publicly traded.

impact on urban credit as most of urban credit does not come under the category of priority sector loans. For example, only 7% of urban lending is agricultural lending. We indeed find this to be true. The results show an average increase of 35% in the amount of loans and an increase of 30% in number of accounts relative to other banks in rural areas. We then conduct sector-wise analysis by splitting the lending into four important sectors - agriculture, industry, personal and trade. Most of the above increase is driven by agricultural lending which forms 53% or rural lending. No corresponding increase occurs for the urban markets, as expected.

Our conjecture is that after alignment the lead banker would work harder and push the loans officers to reach out to more borrowers and disburse more credit. If loan officers are indeed working harder, then average productivity should increase. We find that in rural areas, for aligned banks, credit amount per loan officer increases by 32% and number of accounts per loan officer increases by 28%. What about other drivers of credit such as lower lending rates, liberal screening of borrowers or more loan officers? We find no change in Weighted Average Lending Rate (WALR), ratio of non-performing assets (NPAs) and total number of district-level loan officers for the aligned banks.Thus, the increase in credit supply seems to be mostly driven by increase in effort exerted by the aligned bankers.

To further test for the effort channel, we study the impact of competition on lending by aligned banks. Poaching new customers or expanding to new ones may be difficult if the competitor is a private bank which are more productive relative to public banks. So, if the market share of the private banks is higher, then the marginal benefit of exerting effort may be lower for the employees of the aligned banks and they may be exerting less effort in equilibrium. We test this by including the interaction of alignment variable with the market share of private banks in our bank-district level regressions. Increase in rural lending by the aligned banks and productivity of employees is lower in the districts with higher market share of private banks. This result provides further evidence that the increase in lending by the aligned banks is coming from the effort channel.

We then study if the increase in credit by the aligned Lead Banks translates to an increase in total credit at the district level. For this, we regress credit market variables aggregated upto the district-year level on an indicator of the district being *aligned*. Our specification includes district, year, bank-year and state-year fixed effects which controls for unobserved time-invariant district level, time-varying state and bank-level characteristics. However, we cannot include district-time fixed effects to control unobserved time-varying district level characteristics like demand as it is perfectly collinear with the indicator for alignment of districts. We find an increase in total supply of credit in the aligned districts both at the intensive margin and extensive margin. Sector-wise split suggests an increase in credit in all sectors. No significant change occurs for urban markets. While these results are consistent with our hypothesis, we must mention that these results may be biased because we are unable to control for district level demand.

Finally, we conduct additional tests to check the robustness of our results. We analyse a different specification to test to rule out are any pre-trends in credit disbursal by aligned lead banks. As an alternative identification strategy, we compare treated lead banks against non-treated lead banks from other districts to find expected increase in credit disbursal by treated lead banks. We then look at the impact of alignment on non-lead banks and find no increase in credit as expected. As a placebo test, we study how deposits change because of alignment of lead banks, and find no evidence of increase in deposits. This is expected lines since deposit generation is beyond the scope of Lead Bank scheme.

We make several contributions to the literature. There is a vast literature in banking on the relationship between hierarchy, allocation of control and the use of soft information pertaining to the *ex ante* quality of the borrowers (Stein, 2002; Berger et al., 2005, 2017). Our paper highlights the importance of communicating soft information regarding the *ex-post* unpredictable exogenous factors and how it affects employee performance.

Several papers have shown how giving more authority to the employees can improve their performance (Liberti and Mian, 2009; Liberti, 2017; Skrastins and Vig, 2019; Rodrigo and Nanda, 2012; Qian et al., 2015). Liberti (2017) studies a setting where the authority of some loans officers increased because of change in hierarchical structure in a bank; and this improved their performance. Before the organizational change, loan officers reported to division heads who in turn reported to the corporate head. After the change, some of these loan officers were promoted to senior loan officers and started reporting directly to the corporate head.[3] While delegating more authority to the loan officers would certainly lead to improvement in performance, we discover a complementary channel. If the corporate head (and not the division head) is responsible for decisions regarding the compensation and promotion of the loan officers, i.e. he is the boss of the loan officers as per our definition, then the organizational change would also lead to more face-to-face communication between the loan officer and the corporate head. This improved communication can also lead to improved performance of the loan officers as per the mechanism highlighted in our paper.

The paper also contributes to the literature on the relationship between incentive structure and use of soft information. Heider and Inderst (2012) and Agarwal and Ben-David (2018) show that altering incentive structure to be more volume-sensitive can reduce the use

[3] Liberti (2017) refers to this change as delegation of formal authority. Their sample of treated loan officers also consists of other loan officers who continued to report to division heads, but now the division heads had less time to monitor these loans officers. This case is referred to as delegation of real authority. Our communication channel may not be at work for these loan officers.

of soft information regarding loan quality.[4] We explore the relationship in the other direction: the ability to use soft information regarding *ex post* shocks, which affect outcomes, can help design better incentive structures and increase productivity.

We add to the empirical literature on the trade-off between risk and incentives in agency theory and of the informativeness principle (Holmström, 1979). Aggarwal and Samwick (1999) show that pay-performance sensitivity is lower for executives in firms with more volatile stock prices.[5] Shearer (2004) and Paarsch and Shearer (1999) find that controlling for the variance in exogenous shock, higher incentives can lead to higher effort. Our paper tests another prediction of the theory: if the measurement of employee performance improves, then the effort by the employee will increase. While we do not observe the contracts offered to the employees, which in our case is anyway implicit in nature, we do provide evidence that agents exert higher effort after the principal observes soft information on the effort.

The subject of credit inclusion for small, marginalised sections in India has received considerable attention. Lead Bank Scheme originated during the social banking period with the aim of extending credit to under-represented sections. The early impact of social banking period has been well-recorded (Burgess and Pande, 2005; Burgess et al., 2005; Cole, 2009). We add to this literature by studying the organization design of the Lead Bank Scheme over a more recent period. Our results show how effective information exchange within the organization can yield higher credit deliver at the district-level.

The rest of the paper is as follows. Section two discusses the Lead Bank scheme in India and describes the institutional setting. Sections 3 builds a small model to highlight our effort channel. Section 4 describes the data. Section 5 shows the results at bank-district level and section 6 shows the results at the district level. Section 8 shows the mechanisms and section 9 conducts some robustness tests. Finally, section 9 concludes.

2 Lead Bank Scheme

The Lead Bank Scheme was introduced in 1969 to address geographic disparity in credit availability in India. Concerned by the under-representation of agricultural and small industries sector from credit markets, Reserve Bank of India (RBI) adopted a service area approach where, one commercial bank in each district is assigned the role to promote credit supply in the local market (Gadgil, 1969). This commercial bank is known as the Lead Bank of the district.

[4]For more on agency problems within banks, see Hertzberg et al. (2010), Berg et al. (2020), BhowaL and Subramaniam (2021), among others.

[5]Also see Angelis and Grinstein (2015) and Edmans et al. (2017)

The lead banks assign dedicated personnel whom we refer to the Lead Bank manager or Lead Banker to oversee the lead bank bank activities in their districts. In order to monitor the activities of Lead Banks within a state, RBI appointed another public sector bank to each state in 1977. This bank is known as the Convener Bank of the state. The convener banks monitor the lead banks by conducting quarterly meetings with the lead bank managers. These meetings are headed by the CEO of the convener bank. Convener Bank of a state and all the Lead Banks of districts in the state collectively form the State-Level Bankers' Committee (SLBC). Currently, 28 banks have been assigned the responsibilities of Lead and Convener for all the districts and states in India.

2.1 Activities of Lead Banks

Lead Banks primary roles are guided by the Master Circular released by RBI at regular intervals[6]. Briefly, the role includes promoting credit inclusion in the assigned districts. In order to do so, the Lead Banks conduct the following actions:

1. **Priority Sector Lending**: As per RBI's regulations, 40% of each bank's Adjusted Net Bank Credit is reserved for priority sectors such as agriculture, MSMEs, education etc.[7] Under this program, each district receives an annual credit plan, which is further segregated by each bank within the districts. Lead Banks personnel play a crucial role in implementation of these district credit plans. Given its position in the market, Lead Bank can encourage more effort from own bank personnel toward meeting the assigned priority sector lending targets.

2. **Coordination with Other Banks**: All banks in the districts, and not just the Lead Banks, receive a target under the annual credit plan. Lead Banks coordinate and encourage with other financial institutions in the districts. These efforts occur through various sub-committees between the banks on subjects ranging from increasing lending to agriculture, increasing digital payments, and targeting small-scale industry. Lead Banks also interact closely with high ranking government officials, through various fora, through which Lead Banks inform government agents about the institutional and infrastructural bottlenecks faced by banks.

3. **Public Outreach**: Another role for Lead Banks assigned by RBI is to conduct public outreach programs on financial literacy. For example, Lead Banks in Odisha organized credit *melas* in 6 districts from October 3rd to October 2019 (Odisha, 2019), where

[6] See Master Circular Lead Bank Scheme.
[7] See Banerjee et al. (2004)

bank employees conducted programs on financial literacy. Further, many of these camps are targeted for under-covered or uncovered sections of the societies such as farmers, women, and senior citizens.

2.2 Appointment of Lead Banks and Convener Banks

RBI has adopted the following criteria in choosing a bank as a Lead Bank of a given district (RBI, 1972).

- Number of branches of the bank—The bank which has higher number of branches in the district receives priority in being appointed as Lead Bank of the district.
- Resources of the bank in the district—For resources, assets and liabilities are taken into account while selecting a Lead Bank for a district.
- Contiguity of districts with the same Lead Bank—As much as it is possible, RBI tries to ensure neighbouring districts receive same Lead Bank to the extent possible.

For selecting a Convener Bank, RBI considers the regional orientation of the bank. For example, when the state of Telangana was formed out of Andhra Pradesh in 2014, its convenership was allotted to State Bank of Hyderabad, whereas Andhra Bank was retained as the Convener Bank of Andhra Pradesh. Map of districts and state tagged by their Lead and Convener Bank, respectively, can be found here.

Thus, Lead and Convener Bank appointment is not driven by district-level demand factors but mostly by supply-side capabilities of the bank.

2.3 Incentives for Lead Bank Managers

In most cases, the Lead Bank operations in a district is led by a Chief Manager-level employee of a public sector bank. This employee has an experience of more than 15 years and is a dedicated personnel engaged specifically for Lead Bank scheme activities. Most public sector banks in India have only one port of entry, observe low exit or attrition rate and exhibit rare or almost non-existent lateral entries (Bhatt, 2012). Lead Bank managers are therefore mid-to-high level employees who have climbed up the organization ladder for more than 15 years. Doeringer et al. (1972), and more recently Friedrich (2015), have noted that for employees in such an organizational environment, separation probability from the firm is low. So the incentives for these employees comes from promotions, bonuses and appointments in coveted places or departments within the bank.

The promotions and rewards in these banks, particularly at higher levels, are determined by the recommendations of senior officers ((Chowdary et al., 2013; Singh and Priyanka, 2016).) Further, performance-based bonuses and incentive pay form upto 40% of the compensation for Chief-Manager in these banks (Khandelwal, 2010). Recommendation have also been made to reserve 25% of all bonuses for employees engaged in financial inclusion activity, and Lead Bank personnel clearly come under this category. Thus a lead bank manager would want to be in the good books of his CEO as it can help him get promoted, achieve a coveted appointment or get a higher bonus.

2.4 Alignment, communication and lead bank performance

Given the organization structure of the Lead Bank Scheme, we define the following. A district is *aligned* if the Lead Bank of that district and the Convener Bank of the state in which that district is located are the same banks. A Lead Bank of an aligned district is an *aligned Lead Bank*.

As mentioned above, the CEO of the convener bank conducts quarterly meetings (SLBC meetings) with all the Lead Bank managers in the state to monitor their performance. Thus, if a district is aligned, then the lead banker in the district gets an opportunity to interact with the CEO of his own bank every quarter and explain his performance. These face-to-face interactions give him an opportunity to convey soft information regarding his performance (see examples below) to his CEO, which he would not have been able to communicate if the district was not aligned.

As Dewatripont and Tirole (2005) have argued, information is neither soft nor hard but somewhere in between. More importantly, the softness of information is endogenous and depends on the communication effort of the sender and the attention effort of the receiver. There are several reasons why these SLBC meetings help in communicating soft information. First, in a complex vast market like India, the CEO of the convener banks which are generally very large is likely to be attention constrained (Sims, 2003). So, while the lead banker in a non-aligned district can write a report and send it to the CEO explaining his performance, the CEO may not have the time to read it. She may also find it hard to verify if all the facts mentioned in the report are true or not. The SLBC meetings provide a setting where the lead banker can convey directly about local factors which may be affecting his performance, and what he says is often verifiable because local government officers from other departments, who can check the veracity of what he is saying, are also present in these meetings. Finally, Dewatripont and Tirole (2005) have shown that effort exerted by parties in communicating with each other is higher if their objectives are more aligned. When a district is aligned (non-aligned), then objectives of the lead banker and CEO of the convener bank will be more (less) congruent because they belong to the same (different) bank. So the lead banker will exert more communication effort and the CEO of convener banks will exert more attention effort in an aligned district compared to a non-aligned district. This enables the lead banker to communicate soft information to his CEO.

We provide some examples of soft information communication to the CEO of the convener banks below.[8] It is hard for the CEO to learn and verify such information without being herself present in the SLBC meetings.

i. In the Jharkhand SLBC meetings conducted in March 2012, bankers discussed recent decisions of the High Court of Jharkhand which prevented using land as mortgage under certain situations. This prevented banks from disbursing credit and restricted them from selling mortgaged property to recover asset dues. In the subsequent quarterly meeting of Jharkhand SLBC, government officials informed how land records in four districts are being udpated while for the remaining, the work was in progress. Thus, Convenor bank could observe not only negative shocks in the market, but also subsequent redressal measures.

ii. In November 2019, lead bankers in the state of Madhya Pradesh indicated bureaucratic hurdles from municipal corporations which prevented credit delivery to economically weaker sections (MP, 2019). The information conveyed by the district managers were credible since government representative present in the meetings affirmed these concerns.

iii. In the SLBC meeting conducted in the state of Kerala in 2020 (CanaraBank (2020)), the lead bankers noted the difficulty in lending to small entrepreneurs due to delays in clearance from Pollution Control Board.

iv. Maharashtra SLBC convened a special meeting in June 2011 to discuss agri-loans expansion during the crop sowing season. Bankers informed that they were understaffed to distribute loans to reach out to individual farmers, and thus, be allowed to lend to farmer cooperative societies which then distribute the loans onward. However, this proposal was rejected by government officials on the ground that cooperative banks already lend to cooperative groups. In the end, the bankers were instructed to lend directly to farmers. This discussion indicates the difficulties that bankers face.

[8] These examples are available from the minutes of meeting from SLBC quarterly meetings which are available from SLBC websites.

This ability to communicate such information to the CEO of his bank can affect the effort exerted and performance of the lead bankers. The CEO of the convener bank in the aligned districts, after learning about such factors which affect the performance of lead bankers but are beyond his control, can reward him appropriately by accounting for these exogenous shocks. In non-aligned districts, the CEO of the convener bank cannot reward the lead bankers as they are from a different bank. Thus, using the informativeness principle (Holmström, 1979), the CEOs in the aligned districts offers an implicit *ex ante* contract which incentivizes the lead bankers to exert more effort and shares more risk. Therefore, our hypothesis is that credit delivery by the lead banks will be higher when they are aligned that when they are not aligned.

The next section presents a simple textbook style theoretical model to rationalize these arguments.

3 Theoretical Framework

The basic idea of our theory is very simple. We illustrate the intuition using a standard textbook model where the employee who is the agent is risk averse with CARA preference. Since we use a textbook model, we simply state the results without deriving them.[9] There is a principle (the boss) who hires the employee to exert effort and rewards him with linear wage contract. Effort is denoted by a. Output, q, is equal to effort plus noise: $q = a + \epsilon$, where epsilon is normally distributed with mean zero and variance σ^2. This random error is soft information which can be communicated through face to face interactions. The utility of the agent is given by

$$u(w, a) = -e^{-\eta[w-\psi(a)]}$$

where $\psi(a) = \frac{1}{2}ca^2$ is the cost of exerting effort and $\eta > 0$ is the agent's coefficient of absolute risk aversion.

First we assume the principle does not know ϵ. This is analogous to the case where the banks are not aligned, hence the employee does not get to interact with the CEO and convey ϵ. The wage is then given by

$$w = t + sq$$

where t is the fixed component and sq is the variable component which depends on output. The reservation wage of the employee is given $\bar{w}$. The CEO offers the wage contract to maximize the profit subject to the participation constraint and the incentive compatibility constraint of the employee. We get the following result.

[9] For details, see Bolton and Deatripont (2004).

Proposition 1. In the optimal contract, $a = s/c$ and

$$s = \frac{1}{1 + \eta c \sigma^2}.$$

When the agent can communicate ϵ, by informativeness principle, the principle will offer a contract which is also contingent on ϵ and the wage is now given by

$$w = t + sq + r\epsilon.$$

In this scenario, it can be shown that the optimal contract is such that $r = -s$. Therefore wage is given by

$$w = t + s(q - \epsilon) = t + sa.$$

Thus the principle fully insures the employee. We get the following result.

Proposition 2. In the optimal contract, $a = s/c$ and $s = -r = 1$.

When the employee is able to convey ϵ to the CEO, the CEO can fully insure the employee against this idiosyncratic risk, and so offers the employee a contract which elicits higher effort and shares more risk. Thus the aligned employees are more productive.

4 Data and Summary Statistics

We use Basic Statistical Returns (BSR) Data provided to us by the Reserve Bank of India. This dataset provides branch-level credit and deposit statistics of scheduled commercial banks and regional rural banks in India from 1999-2016.[10] Since our treatment is at the bank-district-year level, so we consider bank-district-year as the unit of observation for our analysis (Donald and Lang, 2007). We observe the number of accounts and the total amount of loans or credit outstanding in a given year by each branch across sectors (agricultural, industry, transport, professional services, trade, etc.) and population centers (rural, semi-urban, urban and metropolitan).[11] We can also observe metrics of asset quality such as weighted average lending rates (WALR) and ratio of non-performing assets (NPA). We will

[10] In India the financial year starts on 1st April and ends on 31st March. So we have annual data from March 31, 1999 to March 31, 2016.

[11] According to RBI, rural areas are defined as centres with a population of less than 10,000. Similarly, semi-urban areas are those with population between 10,000 and 100,000, urban areas are those population between 100,000 to 1 million and metropolitan areas are those with population of more than 1 million.

club semi-urban, urban and metropolitan branches together and call them urban branches. We conduct our analysis separately for rural and urban branches for reasons which will be discussed below.

We develop the panel data on alignment by collecting information on Leads and Conveners from websites of various SLBCs. In order to track changes in Leads and Conveners across years, we collect the notifications for Lead Bank Scheme available from RBI's website. Around 44% of districts are aligned. Figure 2 shows the map of districts in India tagged by their status of alignment.

We first look at the distribution of lending by four major sectors- agriculture, industry, personal and trade - in rural and urban branches (Table 1). In rural areas, agricultural lending comprises of 53% (72%) of total amount (accounts) of credit. Contrarily, in urban areas, agricultural lending comprises only of 8% (29%) of total amount (accounts) credit. Industry loans form a larger share in urban areas (45%) than in rural areas (7%).

Table 2 shows the average loan size in urban and rural areas. As expected, average loan size is much larger in urban areas than rural areas. More importantly, even for agricultural sector we see that urban loans are more than twice as large rural loans.

The above statistics suggest that lead bankers will focus mostly on rural areas than urban areas because of following reasons. The main objective of a lead bank is to give out more priority sector loans. Under priority sector lending, banks can lend to several sectors such as agriculture, micro, small and medium enterprises, housing, education, export, etc. However, all these sectors do not get uniform weight. Agriculture should receives 45% of priority sector loans, while 20% is reserved for small industrial units. In addition, within these sectors, attention is paid to financially excluded and weaker sections of the society. Since agricultural credit comprises 53% loans in rural areas and only 8% loans in urban areas, it is natural that the lead banker will focus on rural areas. Further, the average loan size in the agricultural sector is larger in urban areas than rural areas. So the farmers who are taking loans in the urban branches are likely to be well off and with better access to finance. Given the mandate of giving loans to financially excluded and weaker sections, the lead banker is more likely to find untapped markets in rural areas. Hence we expect that as lead banks become aligned, they will give more credit in rural areas than in urban areas.

Table 3 provides the share of credit that the lead banks provide in rural and urban areas. We see that in rural (urban) area leads banks have a markets share of 35.6% (27.1%). This is consistent with the selection of Lead Banks reflecting supply-side orientation of the bank and indicates the capacity of Lead Banks to influence credit delivery in the district.

Finally, table 4 provides the summary statistics of the important variables separately for aligned lead banks, non-aligned lead banks and non-lead banks. On overage the leads banks are much larger than non-lead banks as they lend more and also has higher number of branches. The WALR is quite similar for the lead and non-lead banks. But the non-lead banks have lower NPA ratio. This is because private banks are non-lead banks and they have lower NPA.

5 Empirical Strategy

Our data is rich enough to allow several empirical specifications. We choose the following which, we believe, allows for the most rigour and interpretability to estimate the impact on a bank within a district.

$$y_{bdt} = \beta.\mathbb{1}\{\text{AlignedLead}\}_{bdt} + \phi_{bt} + \phi_{dt} + \phi_{bd} + \epsilon_{bdt} \tag{1}$$

where, y_{bdt} is our dependent variable for bank b in district d in year t. $\mathbb{1}\{AlignedLead\}_{bdt}$ is an indicator which takes value 1 if the lead bank b in district d is aligned in the year t; i.e. the Convener bank is the same as Lead in that district for that year.

Credit market related outcomes of a bank in a given district can be influenced by large number of factors, such as demand and supply for credit, temporal changes within a bank or variation in capacity across banks in the market. We include bank-year, ϕ_{bt}, district-year, ϕ_{dt}, and bank-district, ϕ_{bd}, fixed effects. Inclusion of bank-year dummies addresses time-varying changes for a bank such as organizational changes, lending strategies or bank capital. District-year effects can account for time-varying local demand and supply factors, which can influence credit markets. District-year effects also absorb endogeneity of a district being aligned. Assignment of a bank as the Lead of a district depends on the pre-existing supply-side capacity of the bank in that region. To account for time-invariant resource differentials across banks within the local market, we include bank-district fixed effects. Since Lead banks did not change in the time period of our observations, bank-district effects also account for endogeneity in Lead bank selection.

5.1 Identification

In equation 1, the coefficient on $\mathbb{1}\{\text{AlignedLead}\}_{bdt}$, β, measures the impact of alignment on credit outcomes of a bank in a district. Identification of this impact requires alignment indicator and the unobserved error term, ϵ_{bdt}, to be uncorrelated; i.e. $E(\mathbb{1}\{\text{AlignedLead}\}_{bdt}).\epsilon_{bdt} = 0$ However, the estimate of β would be biased if the change in alignment of a lead bank was influenced by unobservable bank-district-time factors. Thus, it is important to study the reasons for change in alignment.

In the time period of our study, change in alignment occurs due to the following reasons:

1. Formation of a New State—When a new state is formed, it may be assigned a different Convener compared to the mother state. In such cases, the alignment status of districts in new state may change. For the period of this study, four new states were formed—Chattisgarh, Jharkhand, Uttarakhand and Telangana. Each of these states received a new Convener.

2. Change in Convenership of a State—RBI also changed convenorship for Manipur in 2004 from Union Bank of India to State Bank of India.

In total there are 58 districts which change alignment. Out of these 58 districts, there were 44 districts which changed to aligned from non-aligned and 14 districts which changed to non-aligned from aligned.

For the estimate of β in equation 1 to be biased, residual bank-district-year components should influence state-level changes. It seems highly unlikely that a banking unit within a district leads to a change at the state-level. Further, most Lead Banks once appointed do not change and have remained the same since inception of the Lead Bank Scheme.[12] Inclusion of district-year and bank-districts effect account for these factors. Thus, what changes for the Lead Banks is only the opportunity to communicate with own CEO. The indicator for alignment of Lead Bank in a district is, thus, independent of residual component ϵ_{bdt}. However, we also conduct robustness checks to lend weight to our estimation.

6 Results

6.1 Comparing Lead Banks against other banks within districts

As discussed above, priority sector lending is oriented toward rural markets. Thus, we present results separately for rural and urban areas.

Lead-Bank Performance in Rural Markets Panel A of table 5 shows the impact on credit disbursal in rural branches of Lead Banks under equation 1. Column (1) shows that the total credit disbursed by Lead Banks increases by 0.299 log points after alignment. We dis-aggregate the impact across four main sectors which constitute 91% of total credit market in rural branches. For agricultural sector (column 2), the coefficient on Aligned Lead Bank

[12]Some Lead Banks changed due to merger of banks. However, those cases were not responsible for alignment change since the Convener bank of that district was neither of the two merging banks; i.e. alignment remained 0 before and after merger.

is 0.290 with a standard error of 0.12—rural agricultural credit by a Lead Bank increases by 33% after it becomes aligned. Lending for industry also increases by 0.337 log points though the effect is only significant at 10% level. No effect appears for Personal and Trade loans.[13]

Panel B of table 5 shows the impact of alignment on opening of new accounts in rural areas by Lead Banks. Total number of accounts opening increases by 0.263 log points after a Lead Bank becomes aligned. This effect translates into nearly 30%. We also find a significantly positive increase in new accounts for agriculture, industry and personal sectors.

Lead Bank Performance in Urban Markets Though PSL covers the needs of urban areas, as well, PSL oriented sectors such as agriculture occupy a smaller proportion in urban areas. For eg; agriculture credit comprises only 7% share in overall disbursal in urban branches. Thus, we hypothesize small or no impact in urban credit markets. Table 6 shows the results of Lead Bank performance in urban markets. No significant increase occurs for either total credit disbursal or new accounts of Lead Banks in urban areas after alignment.

6.2 Mechanisms

Next we examine the channel that led to increase in credit in rural areas.

6.2.1 Employee Productivity

If our hypothesis is true, then lead banker would work harder and push the loans officers to reach out to more borrowers and disburse more credit. We should then see an increase in productivity of the loans officers in the aligned lead banks. We use two metrics of productivity—ratio of total lending and loan officers, and ratio of total credit accounts and loan officers. Column (1) shows the results for log of ratio of credit and loan officers. The coefficient in column (1) is 0.285 with a standard error of 0.10. Column (2) reports that the corresponding impact on log ratio of number of accounts and loan officers is 24.9%, which is significant at 1% level. These coefficients are very close to those in credit regressions (see table 5), suggesting that almost the entire increase in credit may be driven by increase in loan officer productivity.

6.2.2 Lending Rates

Lower lending rates may also increase credit uptake as opposed to higher effort on the part of loan officers. Column (3) reports the impact on Weighted Average Lending Rate (WALR).

[13] Our choice of clustering standard errors at district level follows from Abadie et al. (2017). Results remain statistically similar if we cluster standard errors within bank-district strata.

The coefficient is -0.051 which is very small and is statistically insignificant.

6.2.3 Effort substitution

While loan officers may increase effort in prospecting for new loans, they might simultaneously also reduce effort in screening or monitoring the loans to increase credit uptake. This will affect the asset quality and the level of non-performing assets. To detect this, we use ratio of Non-Performing Assets (NPAs) as a dependent variable in Column (4). NPAs remain nearly unchanged after the bank becomes aligned, suggesting that loan officers are not reducing their effort in screening or monitoring the loans.

6.2.4 Loan Officers

Finally, in column (5), we report the impact on total number of loan officers appointed in Lead Banks after alignment. The coefficient is 0.014 and the effect is insignificant. This result rules out allotment of more resources to banks after alignment change.

6.2.5 Competition from Private Banks

Another method to test our hypothesis of higher effort would be to check whether the impact of alignment decreases when facing more efficient competitors. This is because any residual demand in the market may already have been fulfilled by the more efficient banks. So the marginal benefit of effort would be lower in such markets resulting in lower effort in equilibrium, which would further reduce any credit increase because of alignment. Given that private sector banks in India are more productive (Sensarma, 2006), in districts with higher share of rural credit provided by private banks, the effect of alignment should be lower. We use the following specification for this hypothesis:

$$\begin{aligned} y_{bdt} = {} & \beta.\mathbb{1}\{\text{Aligned Lead Bank}\}_{bdt} + \gamma.\mathbb{1}\{\text{Aligned Lead Bank}\}_{bdt} \times \%\text{Pvt.Rural Credit} \\ & + \phi_{bt} + \phi_{dt} + \phi_{bd} + \epsilon_{bdt} \end{aligned} \tag{2}$$

Table 8 shows the results for log of credit, log of accounts, log of credit per loan officers and log of account per loan officers in columns (1), (2), (3) and (4) respectively. Across all specifications, the coefficient on Aligned Lead Bank indicator remains significant and positive. However, the interaction of Aligned Lead Bank indicator and share of private sector rural credit is significantly negative. A one percent increase in share of private banks in rural credit attenuates the increase in total credit, total credit per loan officers, total accounts and total accounts per loan officers by 2.5%, 2.3%, 0.9% and 1.3%, respectively. Another implication of this result is the presence of slack or unmet demand in credit markets in India, which is lower when competition from private bank increases.

6.3 District-level Impact

Does alignment of Lead Banks also impact aggregate market outcomes at the district-level? Lead Banks constitute the biggest banking firms in their respective districts In terms of branches, Lead Banks constitute nearly 20-25% share in the districts. Thus, an increase in Lead Bank productivity may have broader impact as well, beyond just the firm. To test for aggregate impact in the district, we use the following specification:

$$y_{dt} = \beta.\mathbb{1}\{\text{AlignedDist}\}_{dt} + \phi_d + \phi_t + \phi_{st} + \epsilon_{dt} \tag{3}$$

$\mathbb{1}\{\text{AlignedDist}\}_{dt}$ is the indicator which takes value 1 if district d is aligned at time t, and 0 otherwise. We include district, year and state-year fixed effects. The coefficient on $\mathbb{1}\{\text{AlignedDist}\}_{dt}$ indicates the impact on y_{dt} when the district becomes aligned. We are unable to include district-year effects since it will be perfectly correlated with $\mathbb{1}\{\text{AlignedDist}\}_{dt}$. This is not a concern if alignment change of a district is uncorrelated with time-varying demand for credit, after including district, year, state-year and bank-year fixed effects. Nevertheless, we acknowledge the absence of controls for demand for banking services may bias the results.[14]

District-level Rural Impact Panel A of table 9 provides the impact on district-level credit disbursal after the district becomes aligned. Total credit disbursal in the district improves by 0.255 log points with the statistically significant impact at 1% level across all sectors. Panel B shows similar results for accounts as well. Total number of accounts increase by 0.207 log points at the district-level with the corresponding impact for agriculture, industry, personal and trade sectors at 0.231, 0.374, 0.079 and 0.125 log points, respectively. As mentioned previously, these effects may be biased without controlling for demand for credit in districts.

District-level Urban Impact We also test for the corresponding equilibrium impact in urban markets. Table 10 provides the results. Similar to what we observed for bank-district effects, we find no district-level impact on higher credit disbursal or number of new accounts as shown in Panels A and B, respectively.

[14]Such a control was possible in equation 1 through the inclusion of district-year effects.

6.4 Implications

There is a vast literature in banking on the relationship between hierarchy, allocation of control and the use of soft information pertaining to the *ex ante* quality of the borrowers. A key result in this literature is that small banks are more efficient at lending to small firms (Stein, 2002; Berger et al., 2005, 2017). The basic idea is that in small banks loan officers have more control which incentivizes them to acquire soft information which is needed to lend to small firms as hard information is unavailable for them. One implication of our paper is that there could be an alternative complementary explanation for why small banks are more efficient at lending to small firms. We base our conjecture on two assumptions – the first pertains to the communication quality within small banks compared to large banks and the second pertains to difference in reasons for failure of small firms compared to large firms.

A small firm can often fail because of *local* unexpected shocks. These local shocks are likely to be soft information in nature. While these shocks may be visible to local loan officer present in the market, it may not be easily transmittable to his boss in a large bank due to its *soft* nature. A key characteristic of soft information is that it requires the knowledge of context to fully understand it (Liberti and Petersen, 2019).[15] In small banks, a loan officer and the CEO are likely to be well-informed about the local economy shocks. This makes conveying the soft information easier. Contrarily, the head of corporate loan desk (the boss) in a large bank present in many geographies would neither have information about local markets, nor the contextual knowledge to understand it. A loan officer operating in a city would be reluctant to give a loan to small local business as he may either not get an opportunity to explain the performance of this loan to his boss because of hierarchical distance; or even if he gets a chance, he may not be able to communicate well because the boss is unaware of the local factors. Thus, better communication within a small bank makes it more efficient at lending to small firms as CEO can offer more efficient contracts with remunerates the loan officers taking into account these unexpected shocks.

On the other hand, a large firm operating across large geographical areas is unlikely to fail because of local shocks, and it can be expected that any exogenous reason for its failure may be more systemic in nature and would also be well documented making it hard information. A loan officer in a large bank would therefore be more willing to lend to this firm, as the boss will be able to understand the systemic shocks with may lead to *ex post* failure of this firm.

[15] According to Liberti and Petersen (2019), "Information that is difficult to completely summarize in a numeric score, that requires a knowledge of its context to fully understand, and that becomes less useful when separated from the environment in which it was collected" can be called as soft information.

7 Robustness Checks

Our estimation requires that the unobserved bank-district-year effects do not influence alignment of districts or its change. Since change in alignment occurs due to state-level factors such as formation of new states, which are plausibly exogenous to local-level factors, we believe that the estimation strategy has credibility. Thus, local-level factors are unlikely to influence alignment. To further validate our results, we provide some robustness checks in this section.

7.1 Pre-Trends in Credit Variables

Pre-existing trends in credit disbursal or account generation may confound our results. Such a trend may occur for various reasons. Lead Bank personnel could have anticipated the change in alignment. There could be unobservable factors unrelated to but coinciding with alignment change which introduce a pre-trend in credit markets. We test this concern by using the following specification:

$$\begin{aligned} y_{bdt} \ = \ & \beta_{-1}\text{Before}^{-1} * \mathbb{1}\{\text{Lead}\}_{bdt} + \beta_0\text{Before}^{0} * \mathbb{1}\{\text{Lead}\}_{bdt} + \\ & \beta_{+1}\text{After}^{+}1 * \mathbb{1}\{\text{Lead}\}_{bdt} + \phi_{bt} + \phi_{dt} + \phi_{bd} + \epsilon_{bdt}. \end{aligned} \tag{4}$$

We replace the $AlignedLead_{bdt}$ dummy in equation 1 with three dummy variables - $Before^0$, $Before^{-1}$ and $After^{+1}$, which, take value 1 for the year of alignment change, exactly one year before the year of alignment change and for all years after the year of alignment change respectively, and 0 otherwise. We interact these variables with the indicator for the lead bank. β_{-1}, β_0 and β_1, therefore, estimate the impact one year before, the year of and the years after alignment change, relative to the years before alignment change. For pre-trends to bias our results upward, we require $\beta_{-1} > 0$.

Table 11 presents the results for equation 4 with log of credit amount disbursed as y_{bdt}. β_{-1} remains statistically insignificant across all columns, indicating that credit disbursal for any sector by Lead Banks immediately before alignment change was not different from the years prior to that. Importantly, we also find β_0 to be statistically indistinguishable from 0, which indicates that the impact of alignment does not occur instantly. There may be two possible reasons for this. First, some changes in alignment may have occurred in the middle of the year, and so there is not enough time to see the impact in the same year. Secondly, it may take time for the lead banker to push his loan officers to disburse more credit.

In table 12, we use log of accounts as the dependent variable for equation 4. We find β_{-1}

insignificant for the number of total, agricultural and industry accounts. For personal and trade sectors, there exist some pre-trends but the effect is negative.

7.2 Comparison of Lead Banks across districts

Specification in equation 1 provides the impact on Lead Banks with respect to all other banks within districts which received the treatment of alignment change. As an alternative strategy, we compare treated Lead Banks against Lead Banks in other districts. The Lead Banks in other districts did not change alignment, i.e. they were either aligned or non-aligned throughout our sample. Thus, all the other Lead Banks serve as a control group for the treated Lead Banks. Panel A and B of table 13 provides the results on credit and amount for this quasi-experiment. We restrict our sample to rural areas and control for district, state-year and bank-year effects.[16] Consistent with our hypothesis, we find that the Lead Banks increase total credit disbursal by 0.118 log points and agricultural credit by 0.151 log points. Trade sector loans have statistically strong results as well. For total number of accounts and agricultural accounts, we see an increase of 0.113 and 0.101 log points, respectively.

7.3 Comparison of Non-Lead Banks across districts

Non-lead banks do not attend quarterly meetings, and thus do not have the opportunity to communicate even if own CEO is attending. Thus, we expect these banks to not experience any effect due to alignment change. To test that, we restrict our sample to non-lead bank district observations, and compare non-lead banks of districts where alignment changes against non-lead banks of other districts. We regress credit and accounts on the alignment indicator for the district. Table 14 shows the results for amount and accounts for non-lead banks. Each regression controls for district, state-year and bank-year fixed effects. As expected, we see null effects in every regression. These results also rule out any negative spillover on the competitors in the market.

7.4 Impact on Deposits

Credit delivery is the main goal under the Lead Bank Scheme. As a placebo check, we look at whether the deposits get affected too. Table 15 shows that the deposits remain unaffected

[16]This specification has similar concerns as in equation 4; i.e. we are unable to control district-year effects since they will be perfectly collinear with the treatment variable. This will not be a concern as long as unobserved temporal demand is uncorrelated with change in alignment status.

due to the change in alignment. This is unsurprising since Lead Bank personnel are unlikely to exert effort in mobilizing fund intake.

8 Conclusion

Employees have an incentive to exert higher effort when they are assured of a fair assessment of performance. However, assessing the performance of an employee requires sound communication by the employee to his boss. In this paper, we highlight how communication of soft information on exogenous shocks to performance can improve productivity, even if no change occurs in the decision making authority. We analyze the Lead Bank Scheme of the RBI, which aims at expanding district-level credit oriented toward some priority sectors. Under this scheme, RBI assigns plan implementation responsibilities to employees of one bank in each district, known as Lead Bank. Lead Bank personnel of a state convey the problems and challenges faced in their tasks in quarterly meetings. RBI assigns the responsibility of overseeing and conducting these meetings to the CEO of another bank, known as the Convenor of the state. In some districts, therefore, Lead Bank personnel communicate their problems to own CEO, while in other districts the Lead Bank personnel and the Convenor belong to different banks.

We define the districts where Lead and Convenor belong to the same bank, as aligned districts. The theoretical framework in section 3 models how effort and expected output will be higher in the case of Aligned districts. Exogenous factors, such as local demand, ex-post productivity shocks to borrowers, bureaucratic delays and infrastructure bottlenecks, become easier for Lead Bank personnel to convey to the CEO when the district is aligned. This additional information, then, allows the CEO to observe the effort of the Lead Bank personnel more precisely, which induces more effort from the district-level bank officers.

To empirically test this theory, we exploit exogenous changes in the alignment status of a Lead Bank. While this change in alignment does changes the ability of the lead banker to communicate with his CEO, it does not change his decision-making authority. We use the BSR data from RBI to observe credit disbursal from banks. At the bank-district level i.e. the level of intervention of the Lead Bank Scheme, credit inclusion in rural areas increase by 35% and 30% at the intensive and extensive margin, respectively. Further, consistent with the sectoral focus of the priority sector lending, most of the credit expansion occurs in the agricultural sector. We test for various drivers of credit markets. While productivity metrics of credit and accounts per loan officers improve after change in alignment, other drivers which may affect supply of credit, such as lending rates, asset quality, and the total number of loan officers, remain unchanged. These tests validate our hypothesis that when the lead banker is able to communicate with the CEO, he exerts more effort and pushes the loans officers to give out more credit.

Our results also provide interesting implications regarding the banking industry in India. Good management practices can improve performance of firms in developing countries (Bloom et al., 2010; Bloom and Reenen, 2010; Bender et al., 2016). The banking industry in India has also received attention from this debate (Khandelwal, 2010). Broadly, our results suggest that if banks can improve communication of soft information and make decisions contingent on them, then it can lead to increase in productivity. However, the net benefit would require balancing these rewards against the time and attention cost of the CEO, which is beyond the scope of the paper. Understanding this trade-off holistically may provide valuable insights into organizational design of banks in India.

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Appendix

A.1 Figures

Figure 1: Definition

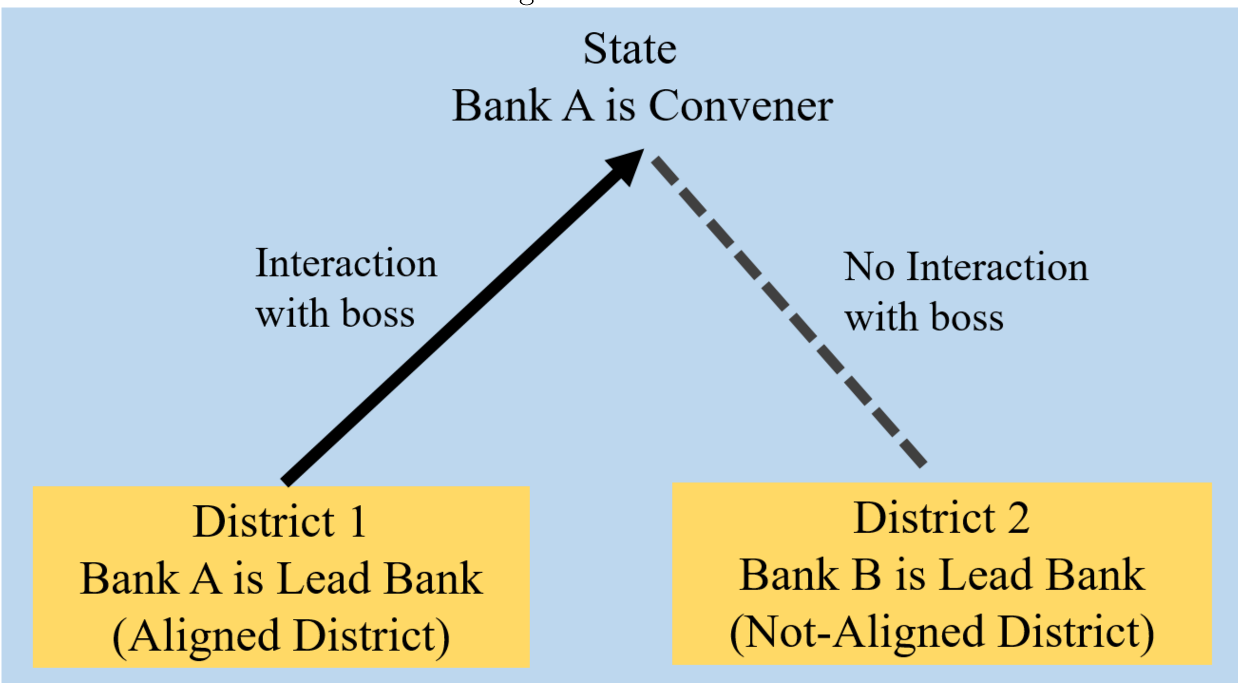
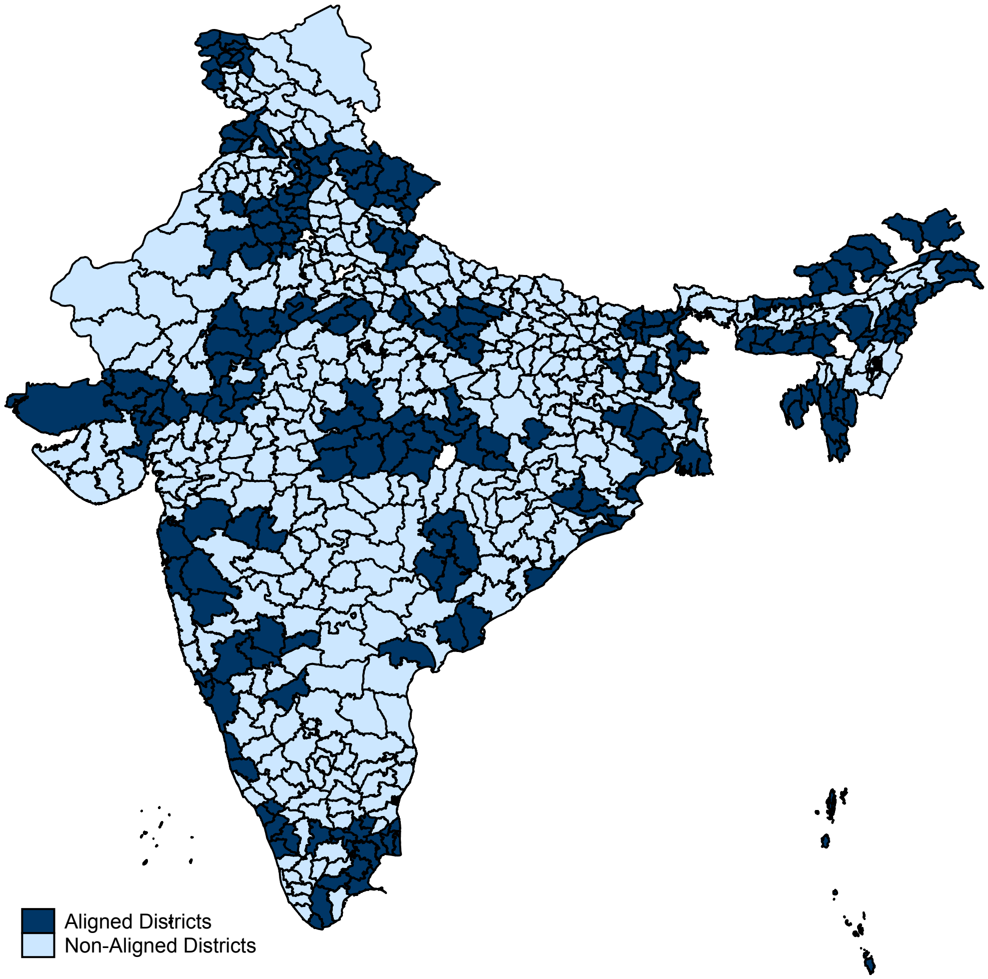


Figure 2: Districts by Alignment



A.2 Tables

Table 1: Sectoral Share- Mean (in %)

	(1) Agri	(2) Industry	(3) Personal	(4) Trade
Panel A: Credit				
Rural	53.28	7.05	16.84	15.72
Urban	7.94	44.58	16.34	9.42
Panel B: Accounts				
Rural	72.37	1.96	12.61	6.13
Urban	29.39	3.24	51.59	5.54

This table calculates each sector's credit share as a % of total credit in Panel A for both Rural and Urban subsamples. Panel B reports the share in terms of number of accounts.

Table 2: Average Loan Size

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Rural	70.4	57.6	129.2	89.7	123.4
Urban	416.4	128.7	4719.2	139.3	636.1

Average loan size for all loans is calculated by regions - Rural & Urban in column 1, and then it is further segregated by the various sectors- Agriculture, Industry, Personal and Trade.Note that this number is in INR thousands.

Table 3: Lead Banks Share- Mean (in %)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Credit					
Rural	35.6	35.3	35.5	35.5	35.1
Urban	27.1	27.9	26.8	26.7	25.3
Panel B: Accounts					
Rural	32.4	33.1	30.5	32.5	30.9
Urban	26.4	28.4	25.5	26.0	24.5

Lead Banks' average lending share in terms of Credit Amount (Panel A) and Credit Account (Panel B) is reported by regions and sectors.

Table 4: Summary Statistics

	Rural			Urban		
	(1) Aligned Lead	(2) Non-Aligned Lead	(3) Non-Lead	(4) Aligned Lead	(5) Non-Aligned Lead	(6) Non-Lead
Credit	1047.8	1172.5	413.8	2466.7	7444.0	2384.3
(INR million)	(1792.1)	(1702.3)	(1596.0)	(5744.5)	(52795.8)	(21984.9)
Accounts	13236.6	16725.1	5953.0	12550.9	15686.5	5669.0
	(16764.8)	(17127.3)	(13033.4)	(19825.3)	(21564.1)	(103702.6)
Loan Officers	27.83	31.78	12.34	39.70	62.28	24.34
	(25.40)	(25.78)	(19.68)	(48.03)	(195.4)	(139.4)
WALR	11.82	11.78	11.82	12.14	12.30	12.40
	(1.688)	(1.678)	(2.694)	(1.838)	(1.690)	(2.503)
NPA ratio	0.0763	0.0811	0.0709	0.0773	0.0792	0.0647
	(0.115)	(0.114)	(0.132)	(0.115)	(0.112)	(0.126)
Branches	13.31	14.79	6.231	9.427	12.25	4.198
	(11.24)	(10.77)	(10.01)	(12.10)	(17.89)	(8.415)

The table reports summary statistics for different subsamples - 1. Lead Banks in Aligned Districts , 2. Lead Banks in Non-Aligned districts , and 3. Non-Lead Banks. The first three columns (1)-(3) correspond to Rural areas, and (4)-(6) correspond to Urban subsample. Note that the variable Credit is reported in INR millions.

Table 5: Bank-District Impact (Only Rural)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedLead_{bdt}$	0.299***	0.290**	0.337*	0.136	-0.120
	(0.09)	(0.12)	(0.18)	(0.13)	(0.22)
Observations	83101	83101	83101	83101	83101
R-Squared	0.932	0.885	0.787	0.889	0.808
Panel B: Log(1+NOAC)					
$AlignedLead_{bdt}$	0.263***	0.235**	0.298***	0.175*	-0.060
	(0.08)	(0.10)	(0.11)	(0.10)	(0.12)
Observations	83101	83101	83101	83101	83101
R-Squared	0.949	0.926	0.870	0.910	0.890
Bank-Year FE	Y	Y	Y	Y	Y
District-Year FE	Y	Y	Y	Y	Y
Bank-District FE	Y	Y	Y	Y	Y

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove the effect of outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 6: Bank-District Impact (Only Urban)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedLead_{bdt}$	0.075	-0.005	-0.025	-0.133	0.052
	(0.08)	(0.16)	(0.17)	(0.09)	(0.13)
Observations	179906	179906	179906	179906	179906
R-Squared	0.921	0.834	0.865	0.904	0.853
Panel B: Log(1+NOAC)					
$AlignedLead_{bdt}$	0.037	0.051	0.142	-0.106	0.030
	(0.08)	(0.13)	(0.10)	(0.07)	(0.08)
Observations	179906	179906	179906	179906	179906
R-Squared	0.931	0.887	0.868	0.919	0.885
Bank-Year FE	Y	Y	Y	Y	Y
District-Year FE	Y	Y	Y	Y	Y
Bank-District FE	Y	Y	Y	Y	Y

Sample restricted to urban areas. Sample is trimmed at 1 and 99 percentile to remove the effect of outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Standard errors are clustered at the district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 7: Drivers of Credit Markets

	Log (Credit/LO)	Log(Accounts/LO)	WALR	NPA Ratio	Log(1+ LO)
$AlignedLead_{bdt}$	0.285***	0.249***	-0.051	0.012	0.014
	(0.08)	(0.06)	(0.14)	(0.02)	(0.05)
Observations	82997	82997	82186	82256	82997
R-Squared	0.890	0.939	0.848	0.512	0.956
Bank-Time FE	Yes	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes	Yes
Bank-District FE	Yes	Yes	Yes	Yes	Yes

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Following Abadie et al. (2017), standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 8: Alignment Effect in Markets with Efficient Competitor

	Log(Credit)	Log(1+NoACs)	Log(Credit/LO)	Log(1+NoACs/LO)
$AlignedLead_{bdt}$	0.311***	0.271***	0.310***	0.271***
	(0.09)	(0.08)	(0.08)	(0.06)
$AlignedLead_{bdt}$ ×	-0.019***	-0.014***	-0.016***	-0.011***
% Rural Lending by Pvt.	(0.01)	(0.00)	(0.00)	(0.00)
Observations	83101	83101	82997	82997
Bank-Time FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
Bank-District FE	Yes	Yes	Yes	Yes

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Following Abadie et al. (2017), standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 9: District-Level Impact (Only Rural)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedDist_{dt}$	0.320**	0.208**	0.487**	0.391	0.267**
	(0.14)	(0.10)	(0.19)	(0.24)	(0.12)
Observations	10590	10590	10590	10590	10590
R-Squared	0.970	0.969	0.860	0.950	0.897
Panel B: Log(1+NOAC)					
	Total	Agri	Industry	Personal	Trade
$AlignedDist_{dt}$	0.207***	0.184***	0.307***	0.287*	0.117**
	(0.07)	(0.06)	(0.10)	(0.17)	(0.06)
Observations	10590	10590	10590	10590	10590
R-Squared	0.970	0.967	0.869	0.919	0.933

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls district, year and state-year fixed effects. We include coefficients on district-year fixed effects from equation 1 as proxy for time-varying demand for financial services in the district. Following Abadie et al. (2017), standard errors are clustered at the district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 10: District-Level Impact (Only Urban)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedDist_{dt}$	0.007	0.010	0.047	-0.124	-0.160
	(0.03)	(0.08)	(0.07)	(0.12)	(0.17)
Observations	10241	10241	10241	10241	10241
R-Squared	0.987	0.971	0.966	0.984	0.968
Panel B: Log(1+NOAC)					
	Total	Agri	Industry	Personal	Trade
$AlignedDist_{dt}$	-0.009	0.078	0.043	-0.123	-0.124
	(0.03)	(0.08)	(0.06)	(0.13)	(0.18)
Observations	10241	10241	10241	10241	10241
R-Squared	0.980	0.967	0.925	0.975	0.947

Sample restricted to urban areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls district, year and state-year fixed effects. We include coefficients on district-year fixed effects from equation 1 as proxy for time-varying demand for financial services in the district. Following Abadie et al. (2017), standard errors are clustered at the district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 11: Pre-Trend Analysis for Amount (Only Rural)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
$Before^{-1}$	0.024	0.133	-0.052	-0.081	0.086
	(0.08)	(0.12)	(0.18)	(0.10)	(0.17)
$Before^{0}$	0.115	0.103	0.093	-0.064	0.153
	(0.09)	(0.13)	(0.24)	(0.11)	(0.24)
$After^{+}1$	0.291***	0.268*	0.196	0.174	-0.347
	(0.10)	(0.14)	(0.21)	(0.14)	(0.27)
Observations	83394	83394	83394	83394	83394
R-Squared	0.939	0.890	0.786	0.892	0.810
Bank-Time FE	Y	Y	Y	Y	Y
District-Time FE	Y	Y	Y	Y	Y
Bank-District FE	Y	Y	Y	Y	Y

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Following Abadie et al. (2017), standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 12: Pre-Trend Analysis for Accounts (Only Rural)

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
$Before^{-1}$	-0.003	0.104	-0.021	-0.178**	-0.161*
	(0.07)	(0.09)	(0.12)	(0.08)	(0.09)
$Before^{0}$	0.107	0.115	0.130	-0.107	-0.077
	(0.07)	(0.10)	(0.14)	(0.09)	(0.14)
$After^{+1}$	0.273***	0.263**	0.237**	0.186*	-0.232*
	(0.08)	(0.11)	(0.11)	(0.11)	(0.13)
Observations	83394	83394	83394	83394	83394
R-Squared	0.953	0.929	0.871	0.911	0.890
Bank-Time FE	Y	Y	Y	Y	Y
District-Time FE	Y	Y	Y	Y	Y
Bank-District FE	Y	Y	Y	Y	Y

Sample restricted to rural areas. Sample is trimmed at 1 and 99 percentile to remove outliers. Each specification controls for bank-district, bank-year and district-year fixed effects. Following Abadie et al. (2017), standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 13: Comparison of Lead Banks across districts

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedDist_{dt}$	0.124**	0.142*	-0.065	0.034	0.076
	(0.06)	(0.08)	(0.16)	(0.07)	(0.12)
Observations	10207	10207	10207	10207	10207
R-Squared	0.958	0.951	0.793	0.892	0.823
Panel B: Log(1+NOAC)					
$AlignedDist_{dt}$	0.113***	0.118**	0.096	0.102*	0.077
	(0.04)	(0.06)	(0.09)	(0.06)	(0.09)
Observations	10207	10207	10207	10207	10207
R-Squared	0.955	0.940	0.844	0.880	0.871

Sample restricted to Lead Banks in rural areas. Each specification controls for district, year, state-year and bank-year fixed effects. Standard errors are clustered at the bank-district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 14: Comparison of Non-Lead Banks across districts

	(1) Total	(2) Agri	(3) Industry	(4) Personal	(5) Trade
Panel A: Log (1+Credit)					
$AlignedDist_{dt}$	-0.016	-0.025	0.135	0.033	0.235
	(0.07)	(0.11)	(0.15)	(0.09)	(0.15)
Observations	73221	73221	73221	73221	73221
R-Squared	0.909	0.856	0.737	0.863	0.766
Panel B: Log(1+NOAC)					
	Total	Agri	Industry	Personal	Trade
$AlignedDist_{dt}$	-0.064	-0.018	-0.035	-0.028	0.034
	(0.06)	(0.08)	(0.09)	(0.08)	(0.08)
Observations	73221	73221	73221	73221	73221
R-Squared	0.929	0.903	0.833	0.886	0.860

Sample restricted to non-lead banks in rural areas. Each specification controls for bank-district, bank-year and state-year fixed effects. Standard errors are clustered at the district level. ***/**/* denote significance at the 1/5/10 percent level, respectively.

Table 15: Deposits - Bank District (Only rural)

	(1) Log(Deposits Amount)	(2) Log(Deposit Accounts)
$AlignedLead_{bdt}$	-0.063	-0.008
	(0.06)	(0.05)
Observations	83019	83019
R-Squared	0.962	0.964
Bank-Time FE	Y	Y
District-Time FE	Y	Y
Bank-District FE	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$