Free-riding in Teams*

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Free-riding among teams forms a central tenet underlying economic theories of the firm. Yet, evidence of free-riding *within organizations* is scarce. We provide this evidence using job rotation on agricultural loans provided by an Indian bank. Job rotation creates a situation of team production with sequential inputs and thereby avoids several confounding effects such as peer influence in teams. Agricultural loans in India rely primarily on non-verifiable information. So, job rotation causes free-riding because each loan officer's contribution to output cannot be verified. Using mandatory rotation for identification and loan performance as a verifiable measure of output, we find that free-riding in teams reduces output by at least 10%. Our results cannot be attributed to any peculiarities of Indian banks. We rule out alternative interpretations such as destruction of the borrower-loan officer relationship, complementarities between the tasks, disruption in the loan officer's learning, borrower moral hazard, or corrupt lending practices.

Key Words: Agency Costs, Bank, Default, Free-riding, Information, Loan, Rotation, Teams.
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I Introduction

Motivation: Team production, where output is a function of the efforts of two or more workers, characterizes economic activity of various hues. For instance, work done in most white-collar jobs, some blue-collar jobs, by the Cabinet in a Government and by committees represents team production. A consequence of team production is the potential for free-riding behavior by team members when it is difficult to observe and verify the contribution of each team member. Such free-riding forms the central tenet underlying economic theories of the firm (Alchian and Demsetz (1972), Holmstrom (1982)). Theories that posit various mechanisms to reduce free-riding—monitoring and supervision (Alchian and Demsetz (1972), Jensen and Meckling (1976)), budget breakers (Holmstrom (1982)), peer monitoring (Kandel and Lazear (1992), Carpenter and Matthews (2009)), relational contracts (Rayo (2007)) and verifiable signals (Hölmstrom (1979), Hertzberg, Liberti, and Paravisini (2010))—assume free-riding in teams to be pervasive. Despite its central role in the theory of the firm, evidence of free-riding within organisations is scarce. In this study, we utilise data from a unique organisational setting to provide such evidence.

Lack of evidence of free-riding within organisations is likely due to the several confounding factors that hobble empirical tests of the same. Because members of a team may interact frequently, they may be encouraged to monitor and motivate each other. Moreover, knowing that they have to interact with each other for some time, team members may cooperate with or even train each other (Hamilton, Nickerson, and Owan (2003)). Such "peer effects" may reduce or eliminate the effect of free-riding (Kandel and Lazear (1992), Marks, Babcock, Cillessen, and Crick (2013)). Similarly, the presence of verifiable signals may force team members to avoid free-riding (Hölmstrom (1979), Hertzberg, Liberti, and Paravisini (2010)).

It is also possible that free-riding does not manifest in teams in the first place. Unlike the standard assumption in economics that all work is distasteful, employees may be intrinsically motivated to perform certain kinds of jobs. Such employees would match with firms that offer them the jobs they enjoy. As a result, employees in a team may not shirk (Prendergast (2007)). In fact, human resource practitioners and other social science disciplines view skeptically the standard economic assumption that all work is distasteful (March (1994), Pfeffer (1996), Kreps (1997), Baron and Kreps (1999)).

Ultimately, the question is an empirical one: Does free-riding actually occur in teams? If one could obtain a setting where none of the confounding factors mask its effect, would we actually find free-riding in an organisation? If free-riding does not exist, then theoretical mechanisms postulated in the literature to overcome free-riding may be "shooting flies with a cannon." Conversely, if free-riding does exist, then the true benefits of team incentives and peer effects may be even more than the large positive effects estimated by Hamilton, Nickerson, and Owan (2003), Mas and Moretti (2009)).

The ideal empirical setting: Apart from data inside an organisation, studying this question requires a setting that satisfies the following conditions. First, for comparison, we need the same job to be done by a team in some cases and by an individual in other cases. Relatedly, the choice of team versus individual production should not be endogenous to either team or individual characteristics. Second, none of the confounding factors should pollute the setting. Finally, but most importantly, the setting for team production should be such that it is difficult to observe and verify the contribution of each team member. Otherwise, we do not expect free-riding to manifest in the first place.

Our clean empirical setting: We use job rotation on a sample of agricultural loans provided by a bank in India to generate a clean empirical setup. Performance of bank loans represents a production function that takes two inputs—screening and monitoring. Also, unlike other organisational settings, bank loans generate a verifiable output measure—loan performance. Absent job rotation, one loan officer undertakes screening and monitoring of loans. Job rotation, however, transforms this activity into one of team production—the incumbent screens and originates the loan while the replacement monitors the loan and collects the payment. As Alchian and Demsetz (1972) define, "team production of Z involves at least two inputs X_i and X_j with $\frac{\partial^2 Z}{\partial X_i \partial X_j} \neq 0$" (pp.779). Thus, job rotation provides variation where the two inputs X_i and X_j are provided *sequentially* by one officer in some cases and by a team of two officers in other cases. Because the bank follows a policy of mandatory rotation once the loan officer has completed three years in a branch, the choice of team versus individual production is unrelated to loan officer characteristics or loan performance.

Because the inputs X_i and X_j are sequential and not simultaneous, job rotation removes the effect of other confounding factors in team production. Specifically, the inter-personal interactions that generate peer effects or social pressures in a team setting are absent in job rotation. For instance, without knowing who the replacement officer would be—which is the case when job rotation occurs in a large organisation comprised of a few thousand employees—the incumbent and the replacement cannot cooperate with each other. Nor can they monitor, motivate or train each other.

The sample of agricultural crop loans in India provides a setting where the third criterion for a clean empirical setup is also satisfied. Hertzberg, Liberti, and Paravisini (2010) study the effect of job rotation for term loans to small and mid-size corporations, which involve interim (interest) payments. Also, soft, unverifiable information on the borrower is supplemented by (verifiable) loan documentation. Interim interest payments and (verifiable) loan documentation represent verifiable signals that can an incoming loan officer can use to ferret out free-riding. In contrast, agricultural crop loans in our setting are zero-coupon loans that do not require any interim payments. As well, crop loans are provided by Indian banks to farmers who are mostly illiterate, do not document their activities, do not possess any financial reports and do not pay taxes. Thus, except in the case of repeat loans, loan officers cannot leave any verifiable information that explains their actions. Therefore, job rotation in our setting represents team production where it is difficult to observe and verify the contribution of each team member. So, we expect free-riding in teams on loans affected by job rotation and, conversely, no free-riding in teams on loans not affected by job rotation.

Main results: To test this thesis, we combine exogenous rotations created by mandatory rotation with the important feature that all agricultural crop loans have an *exact maturity of 12 months*. Though scheduled rotation is expected to occur after three years, it varies between 33 to 39 months in practice (due to administrative exigencies). Therefore, loans originated before the 24^{th} month of a loan officer's tenure are extremely unlikely to be affected by rotation. In fact, given that actual tenure could randomly vary between 33 to 39 months, loans originated in the 27^{th} month of a loan officer's tenure may not be affected by rotation. After the 27^{th} month, the probability of a loan being affected by rotation is extremely high. Thus, loans affected by rotation are chosen randomly with the probability changing based on loan officer tenure.

In our initial tests, we use this variation to compare the probability of default on loans originated before and after a particular month of an officer's tenure. In these tests, we use officer and time fixed effects. We find that starting from the 27^{th} month onwards, the loans originated in every month have a progressively higher probability of default than loans originated before. This monotonic increase suggests *free-riding by both the incoming and outgoing loan officers* in screening and monitoring respectively. For loans originated in the 29^{th} (31^{st}) month, the incoming officer is expected to monitor the loan for five (seven) months (using 36 months as the expected tenure). Because any loan originated after the 27^{th} month almost certainly gets affected by rotation, the difference between loans originated in the 29^{th} month and the 31^{st} month does not stem from the probability of rotation. As a result, there cannot be any difference in the quality of screening effort by the outgoing officer either. Therefore, the higher probability of default for loans originated in the 31^{st} month has to stem from free-riding in monitoring effort for seven months instead of five months.

In our subsequent tests, we compare the probability of default on loans originated in the last six months, three months and one month of a loan officer's expected tenure vis-à-vis loans originated earlier. As argued above, these loans are certainly affected by job rotation. Apart from officer and time fixed effects, we separately control for borrower fixed effects, loan level factors and time-varying officer fixed effects as well. We find that the probability of default on loans originated in the last six, three and one month of expected tenure are higher than that on loans originated earlier by 10%, 17% and 21% respectively. As argued above, the difference in the economic magnitudes further supports free-riding by both the incoming and outgoing loan officers.

In additional tests, we exploit the discontinuity provided by the actual date when the loan officer was transferred and compare loans originated just before and after this date (15, 30, 45 and 60 days). These tests allow us to control sharply for any confounding factors that may affect the earlier tests. In line with our main thesis, the probability of default on loans originated immediately before rotation is significantly higher than loans originated immediately after rotation.

For repeat borrowers, prior default represents a verifiable piece of information that the bank possesses. Anticipating that the incoming loan officer can dig out this piece of verifiable information and convey the same to superiors, a loan officer is less likely to provide loans to borrowers that have defaulted on their previous loan at the end of his tenure when compared to the beginning of his tenure. We find that this is indeed the case in our sample, which is consistent with the disciplining effect of job rotation highlighted by Hertzberg, Liberti, and Paravisini (2010).[1] Among other verifiable measures such as the number and amount of loans, we find no differences at the end of an officer's tenure when compared to that before.

Results not due to the incentives in government-owned banks: A key concern stems from the possibility that the incentive structures prevailing in government-owned banks (GOBs hereafter) explain why our findings are different from those in Hertzberg, Liberti, and Paravisini (2010). As we explain in detail in the next section, the differences vis-à-vis Hertzberg, Liberti, and Paravisini (2010) stem from our use of a setting where free-riding is expected in teams. Here, we highlight several reasons why such concerns are unfounded.

First, because our identification strategy exploits variation within the tenure of a loan officer, any time-invariant features cannot explain our results. A residual concern could be that loan officer incentives (other than free-riding in teams) change with rotation. Specifically, the concern could be that the loan officer only cares about meeting a minimum quota of agricultural lending. Therefore, the loan officer picks out the best available projects first and then lends to the marginal projects as his/her term expires. However, all our loans are agricultural crop loans of exactly one-year maturity. So, even if the primary motive of the loan officer is to meet a minimum quota of agricultural lending, the loan officer has to lend to meet a fresh quota in every year of his tenure. Thus, the loan officer cannot inter-temporally substitute loan quality across his entire tenure.

Second, we find results identical to Hertzberg, Liberti, and Paravisini (2010) when we use prior default as a proxy for verifiable information. If our results stemmed from the GOB not caring about default on the loans originated by its loan officers, the positive incentive effects of job rotation highlighted in Hertzberg, Liberti, and Paravisini (2010) should not be obtained either.

Third, existing work focusing on India finds no difference between private sector banks,

[1]Note that because of legal requirements on directed lending to agriculture in the Indian context, loans to defaulted borrowers are not uncommon.

i.e. banks not owned by the Government of India, and GOBs with respect to incentives. For example, Rajan (2009) states that "There is little evidence that government ownership creates deep differences in employee actions and behavior. Indeed, it is increasingly evident that when asked to generate profits, public sector entities do exactly what private sector entities do." Similarly, Cole, Kanz, and Klapper (2015) and Bhaumik, Dang, and Kutan (2011) do not find any difference in the way in which employees of public and private sector bank respond to incentives. This is not surprising because GOBs are run as commercial entitites, where the Government of India owns a majority stake, and not as departments of the Government. Furthermore, as we highlight in section IV.C, loan officers in our setting strongly care about loan performance.

Other alternative explanations: First, job rotation may disrupt any complementarities between screening and monitoring. To show that our results do not stem from this channel, we examine loans that were expected to be—but were not—affected by rotation. In this sample, complementarities between the tasks, if any, are preserved. We find similar deterioration in loan performance due to job rotation in this sample, which suggests that the results do not stem from this alternative explanation.

Second, our results cannot be explained by disruption in the borrower-loan officer relationship due to rotation. To establish this, we contrast the effect of job rotation between (i) loans that were originated by a loan officer that already had a prior relationship with the borrower; and (ii) loans that did not have a prior relationship. We find no difference in the effect of job rotation for these two samples.

Third, our results cannot be explained by borrower moral hazard. For borrower moral hazard due to job rotation to account for our results, borrowers should know when a loan officer is expected to be transferred out of the branch. Borrowers having a relationship with the loan officer are a lot more likely to know this when compared to borrowers not having a relationship with the loan officer. Because our results are no different for loans to borrowers with a prior relationship and borrowers with no prior relationship, borrower moral hazard is unlikely to explain our results.

Fourth, our results cannot be accounted for by loan officers simply enriching themselves at the end of their tenure (by originating bad loans in return for side-payments from the borrowers). We described above that our results manifest from free-riding not only in the quality of screening (by the outgoing loan officer) but also by the intensity of monitoring and loan collection efforts (by the incoming loan officer). If the outgoing loan officers were simply enriching themselves strategically at the end of their tenure, then loan performance cannot be due to free-riding in monitoring effort.[2]

Finally, our results cannot be explained by disruption in the officer's learning due to

[2]Relatedly, our bank has a large organization with branches spread all over India. When loan officers are transferred all over the country at short notice, the incoming and outgoing loan officer cannot collude perfectly to share the spoils from such strategic enrichment.

rotation. To examine this alternative interpretation, we study the effect of job rotation on loans that are affected by *unscheduled* rotation, i.e. loans originated by officers that move before completing their scheduled tenure in their branch. The loans originated by such loan officers are not expect to be affected by rotation. But, they are affected by disruption in officer's learning. If our results stem from disruption in the officer's learning, then we should find loan performance to deteriorate following job rotation for these loans as well. However, we find that job rotation does not affect performance of loans that are affected by unscheduled rotation.

II Review of literature

We contribute primarily to the organizational economics literature by providing evidence of a central tenet underlying economic theories of the firm—free-riding in teams. To our knowledge, ours is the first study to provide evidence *within an organization of free-riding in teams*. Several studies have studied team incentives and found them to be quite effective in laboratory experiments (Dohmen and Falk (2011)), in field studies (Ichniowski, Shaw, and Prennushi (1997), Hamilton, Nickerson, and Owan (2003)) and within organizations (Hertzberg, Liberti, and Paravisini (2010)). While Hertzberg, Liberti, and Paravisini (2010) find positive effects of rotation, we find *negative* effects of the same and thereby highlight free-riding in teams. Hertzberg, Liberti, and Paravisini (2010) study loans to small and mid-sized corporates, where verifiable loan documentation as well as verifiable signals from interim loan payments supplement non-verifiable information. Therefore, the incoming loan officer can ferret out shirking because verifiable information/signal of such shirking is available in their setting. We use an environment where lending is primarily based on non-verifiable information. As a result, free-riding in teams cannot be avoided. Our finding that free-riding indeed occurs in teams *strengthens* the findings in these studies because the true benefits of team incentives, peer effects and verifiable information/signal is likely to be even more than what these studies find if free-riding indeed exists.

We contribute to three other streams of the literature. First, our study relates to the organizational economics literature on job rotation (Hirao (1993), Arya and Mittendorf (2004), Hertzberg, Liberti, and Paravisini (2010) and Di Maggio and Van Alstyne (2012)). We differ from these studies by highlighting free-riding when job rotation occurs in an environment where decision-making is based on non-verifiable information.

Second, we contribute to the financial intermediation literature that (i) examines the effect of incentives in financial intermediation (Agarwal and Hauswald (2010), Agarwal and Ben-David (2014), Cole, Kanz, and Klapper (2015), Berg, Puri, and Rocholl (2013)); and (ii) studies the use in bank lending of non-verifiable and verifiable information, labeled "hard" and "soft" information respectively (Berger and Udell (2002), Stein (2002), Rajan and Zingales (2001), Berger, Miller, Petersen, Rajan, and Stein (2005), DeYoung, Glennon, and Nigro (2008), Liberti and Mian (2009), Agarwal and Hauswald (2010), and Puri, Rocholl, and Steffen (2010)). We contribute to the financial intermediation literature by highlighting the perverse incentives created by job rotation when lending is based on non-verifiable information.

III Theoretical background

We describe the theoretical arguments that allow us to use job rotation in our setting to test for free-riding in teams. As described in the introduction, we study job rotation in a bank for the following reasons. First, loan performance provides a verifiable measure of output within an organisation; such *intra-organisational verifiable measures of output are rarely available in other organisational settings*. Second, job rotation enables us to contrast output from individual production versus output from team production (where the team comprises of the incoming and outgoing loan officers). Finally, because job rotation creates the setting for team production without the attendant inter-personal interactions that are present in other settings, job rotation avoids the various confounding effects we described in the introduction.

To understand the theoretical arguments clearly, consider a principal-agent relationship, where a bank is the principal and loan officer(s) are the agents. Agents exert efforts in screening a borrower and monitoring him. Greater effort by the loan officer in screening the borrower should reduce adverse selection and thereby the probability of the loan defaulting. Similarly, greater effort by the loan officer in monitoring the borrower should reduce moral hazard and thereby the probability of the loan defaulting. Therefore, the principal designs incentives to motivate effort in screening and monitoring borrowers.[3] We describe loan officer incentives in our setting in section IV.C.

The table below distinguishes the effect of job rotation between organisational settings where a verifiable (interim) signal of loan performance is available and situations where such a signal is not available.

Table 1: Free-riding in teams?

		No job rotation $\Rightarrow$ Individual production	Job rotation $\Rightarrow$ Team production
Is a verifiable (interim) signal of loan performance available?	Yes	$\times$	$\times$
	No	$\times$	$\checkmark$

The top row represents organisational settings where a verifiable (intermediate) signal of future loan performance is available. In this case, the firm can combine this signal with

[3] Our setting does not correspond to the multi-tasking set up studied by Holmstrom and Milgrom (1991) because screening and monitoring do not produce measurable output by themselves.

loan performance to design incentives that motivate efforts in screening and monitoring (Hölmstrom (1979)). In a bank, verifiable information about the creditworthiness of the borrower may be available in the form of the past repayment record, tax returns, information gathered from savings/checking accounts of the borrower, etc (Cole, Goldberg, and White (2004), Puri, Rocholl, and Steffen (2010)).

The bottom row represents organisational settings where a verifiable (intermediate) signal of loan performance is not available. In this case, the principal can base the incentive contract only on final loan performance, which is verifiable.

The column on the left represents situations involving individual production because one agent undertakes the job from commencement to completion (because there is no job rotation). In this case, the principal can design an incentive contract based on final loan performance and/or a verifiable (intermediate) signal (if it is available) to motivate effort in screening and monitoring. The column on the right represents situations involving team production because the job gets split between the incoming and the outgoing agents when there is job rotation.

Consider first the cell in the upper-right corner of the table: here team production occurs in settings where a verifiable (interim) signal of output is available. In this case, the signal can enable the incoming agent to verify the effort made by her predecessor. So, the principal obtains an independent verification of effort made by the outgoing agent. The incoming agent is likely to exert the costly effort to verify to avoid being blamed for outcomes that result due to lax effort by the outgoing agent. Of course, she is likely to reveal such information as well. Rationally anticipating such verification, the outgoing agent, who is driven by career concerns, exerts optimum effort in this case. As a result, job rotation does not lead to free-riding when a verifiable (interim) signal of future loan performance is available (Hertzberg, Liberti, and Paravisini (2010)). From the perspective of testing free-riding in teams, we therefore cannot utilise job rotation in settings where a verifiable (interim) signal of loan performance is available. In other words, *the cells in the top row cannot be used to test free-riding in teams.*

In contrast, *the cells in the bottom row can indeed be used to test free-riding in teams.* When job rotation occurs in organisational settings where a verifiable (interim) signal **not** is available, the principal cannot assess the individual contribution made by each agent. This is because the number of verifiable measures available for incentivising performance—loan performance in this case—is less than the number of agents that need to be incentivised—the incoming and outgoing loan officers. Also, the incoming agent cannot verify the effort made by her predecessor because the (interim) verifiable signal of future loan performance is not available. As a consequence, both the incoming and the outgoing agent can pass the buck to the other. Rationally anticipating the principal's difficulty in assessing individual contributions, each agent has the incentive to shirk. Thus, the free-riding in teams problem manifests in the bottom-right cell. However, even though the information structure is identical in the bottom-left cell, free-riding cannot manifest in that case because team production is not involved. Therefore, comparing loan performance between the bottom-left and bottom-right cells can enable us to study free-riding in teams.

Note that unlike Holmstrom (1982), budget breakers are not employed in the bank we study. In fact, as we described in section IV.C, the incentive contracts for loan officers remain unaffected by job rotation.

IV Institutional background

As institutional background for our empirical analysis, we describe agricultural lending in India, the process and nature of information collected by loan officers, and the nature of incentives faced by employees of GOBs in India.

IV.A Agricultural lending in India

As described in the introduction, our empirical analysis focuses on the agricultural loans provided by the lender. Four key factors—non-verifiable information, scarce collateral, state control of banking and poor legal enforcement—characterize the agricultural credit markets in emerging economies like India.

IV.A.1 Importance of non-verifiable (private) information

Agricultural lending in a developing country like India is based primarily on non-verifiable private information. First, apart from routine information such as name, address, etc., the loan officer does not have access to any other relevant verifiable information. Because agricultural income in India is exempt from income tax,[4] small farmers, who do not have any other source of income other than agricultural income, do not file income tax returns. Neither is there any independent audit of the farmers' income. Given that nearly 44.1% of small farmers in India are illiterate (Mahadevan and Suardi, 2013), proper annual records of production are not maintained by small farmers. As well, no publicly available credit history exists for borrowers of agricultural loans in India.[5]

The farmers in our sample are quite small: they have landholding of less than 2 hectares. Small farmers are less likely to use modern technology as these involve fixed costs in learning and in financial investment. Given the size of their landholdings, such fixed costs are disproportionately high. Nearly 65% of the small farmers depend on rain

[4] As per Sec 10(1) of the Income Tax Act 1961, agricultural income is exempt from tax.

[5] India has a credit information bureau named "Credit Information Bureau (India) Limited (CIBIL)." CIBIL needs a unique identifier such as a social security number, income tax number, etc. to link a transaction to an individual. No such unique identifier exists for small and marginal farmers. Therefore, CIBIL does not possess the credit histories of small agricultural borrowers.

fed irrigation (Mahadevan and Suardi, 2013). As well, more than 75% of Indian farmers are not covered by crop insurance (Mahul and Verma, 2012). Thus, a loan officer cannot use potentially verifiable information such as the use of irrigation and/or crop insurance. This deprives the loan officer of any "verifiable" source of information to assess the creditworthiness of an agricultural borrower.

Second, it has been argued in the financial intermediation literature that geographical proximity to the borrower and hierarchical distance, i.e. the difference between the hierarchical level where the authority to approve a loan is vested and the hierarchical level where the loan is screened and monitored, determine crucially the use of verifiable versus non-verifiable information for lending (see Petersen and Rajan (2002), Berger, Miller, Petersen, Rajan, and Stein (2005), Liberti and Mian (2009), Agarwal and Hauswald (2010) among others). Specifically, *ceteris paribus* greater the geographical distance or the hierarchical distance, greater the reliance on verifiable information because of the ease with which verifiable information can be transmitted geographically or across organisational layers and interpreted correctly. All the bank branches we study are rural branches that have only one loan officer—the branch manager—who is assisted by 4-5 clerical staff. We have observed during the data collection exercise that the branch manager meets all the borrowers personally before approving crop loans. The branch manager is located geographically proximate to the borrower and interacts regularly with them. Also, as part of the policy set by the bank, loans below the size of INR 0.65 million can be sanctioned by the branch manager. Because the size of the agricultural crop loans in our sample are much smaller (approximately INR 30,000), the loan officer has the authority to sanction the small sized agricultural crop loans without having to seek the permission of an officer higher in the organizational hierarchy. Thus, the loan officer is fully responsible for all aspects of the loan such as screening, approving, monitoring and collection.

Third, the loans we examine are *bullet loans*, where the borrower repays the loan with accrued interest at the end of 12 months. In other words, no intermediate (coupon) payments are stipulated in the loan contract. Thus, unlike in the case of corporate loans that involve coupon payments, the bank management cannot reward/penalize loan officers based on intermediate payments on the loan.

Finally, the borrowers in our sample do not own a checking or savings account with the bank. This fact reflects the reality of financial exclusion in India where 51% of farmers do not even have a bank account (Karmakar (2008)). The loan officer's interactions with his borrowers are only through the loan account and transactions related to the same.[6] As a result, unlike in Puri, Rocholl, and Steffen (2010), loan officers cannot utilize information

[6] Apart from our observations during the data collection exercise, we have checked this aspect using the detailed transaction level data shared by the bank with us. Because this data enables us to track every transaction undertaken by the bank's customers, we are able to infer that the small farmers that borrow the agricultural crop loans only operate the loan account with the bank and do not have any other account with the bank.

from savings or checking accounts to obtain verifiable information about the borrower.

IV.A.2 Scarce collateral

A common solution to mitigate strategic default is to have the borrower post a physical asset as collateral, which can be appropriated upon default. However, most farmers in emerging economies are too poor to post a collateral other than their land or the crop. Poorly delineated property rights over land exacerbate the problem by making it difficult for the bank to foreclose land put up as collateral. Moreover, foreclosing a farmer's land/crop is extremely politically sensitive as local politicians, cutting across party lines, intervene on behalf of farmers.[7] Effectively, farmers in India do not face the threat of their collateral being taken over by their lenders, which encourages strategic default.

IV.A.3 State controlled banking system

Government of India plays a dominant role in the Indian banking sector. GOBs account for 74.2% (75.1%) of aggregate amount of loans outstanding (deposits) in the banking sector. The Government of India nationalized many private banks in 1969 and in 1980 and enforced several measures with the declared objective of improving access to finance to some "critical" sectors and to vulnerable sections of the population. Priority sector guidelines and branch expansion norms were the most impactful regulations issued (see Burgess and Pande (2005), Burgess, Pande, and Wong (2005), Cole (2009)). Priority sector lending guidelines require by law that 18% of a bank's credit be directed to agriculture and allied activities. Government of India introduced another set of guidelines that required the banks to open branches in four unbanked locations for every branch in a banked location. This substantially increased the branch network and improved access to finance in rural areas (see Burgess and Pande (2005)). As on 31st March, 2013, there were 157 commercial banks operating 104,467 branches in India.[8]

IV.A.4 Poor enforcement

Given state control of banking and the political economy of state controlled lending (see Khwaja and Mian (2005), Cole (2009)), recovery of loans has been a major challenge in India. Though the establishment of debt recovery tribunals and the passage of "Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFAESI)" Act have substantially improved the NPA scenario (see Visaria (2009)), neither of them apply to small agricultural loans. Thus, for agricultural loans, lenders

[7] In one such incident in Mysore, Karnataka, the lender was forced to return the tractor repossessed from a farmer as the farmer committed suicide. The local politicians alleged that the suicide was due to "arm twisting" tactics employed by the recovery agents of the bank. The Hindu, June 30, 2008.

[8] Source:http://rbidocs.rbi.org.in/rdocs/Publications/PDFs/00QSB170913F.pdf

do not have recourse to any special laws and have to rely on courts for enforcement. The slow judicial process compounds lenders' difficulties in loan recovery.[9]

IV.B Non-verifiable information collected by loan officers

We now describe the nature and type of non-verifiable information collected by loan officers and the process through which they collect such information.

IV.B.1 Process of non-verifiable information collected by loan officers

All loan officers in our sample belong to the "manager" cadre. They have usually spent about a decade on the job after starting at the entry level. Before being promoted to the managerial role, they would have handled the screening and monitoring of several loans. Thus, the loan officers have acquired general expertise in the credit operations of the bank by the time they get promoted as managers in a branch.

In our setting, the loan officers acquire specific information about the branch where they are posted through informal interactions. The rural branches of GOBs in India are quite small and comprise of less than 10 employees. Given the small team, informal interactions between the branch manager ("the loan officer" in our case) and employees reporting to him enable the loan officer to acquire specific information about the nature of agricultural production in the area where the branch is located.

An institutional feature of the Indian banking system aids collection of non-verifiable information. As part of the Know Your Customer (KYC) norms, a new borrower needs a formal introduction from an existing borrower in order to open a loan account (Iyer and Puri (2012)). Loan officers therefore spend a lot of time talking to the potential borrower's references. Loan officers also conduct field visits where they talk to the neighbors of a potential borrower. Finally, loan officers also get invited to a number of village level ceremonies, where they get a chance to build social networks. These social networks are particularly useful in screening and monitoring an agricultural borrower.

IV.B.2 Nature of non-verifiable information collected by loan officers

First, loan officers investigate whether the borrower is indeed a genuine farmer or not. Given the heavy subsidies on agricultural loans in India, loan officers have to worry about the possibility of agricultural loans being diverted to other purposes. Ownership of agricultural land does not provide a reliable signal about the same because most village land in India is considered as agricultural land irrespective of its cultivation status. Moreover, no formal records are available about the farmer's past track record for cultivation.

[9] World Bank's doing business survey 2012-2013 ranks India 132 out of 185. With respect to enforcement of contracts, India occupies 17th rank. Also, enforcing a contract in India takes on an average 1420 days when compared to 150 days in Singapore.

Second, the loan officer looks to obtain information about the actual purpose for which the borrower is seeking the agricultural loan. He investigates using his social network if the borrower is planning an important social ceremony (such as the wedding of his/her daughter) because the borrower may be trying to obtain the agricultural loan to fund such social ceremonies. The loan officer also taps into his network to reassure himself that the borrower is not intending to start some other business.

Third, the loan officer collects information about the social networks of a borrower. Given the scarcity of organized markets for agricultural inputs, farmers have to critically rely on strong village-level social connections in order to obtain inputs such as labor, seeds and technological nuances.

Fourth, the loan officer collects information about other members of the (possibly extended) family of the borrower. In India, large, extended families often work on the family farm. Therefore, information about the composition of the family is critical. The loan officer prefers families that possess captive labor (in the form of members from the extended family) to work on agricultural field because this reduces uncertainty about labor inputs to production.

Fifth, loan officers collect information about borrowers' personal addictions such as gambling or alcoholism. They obtain such information using their social networks.

Finally, loan officers utilise their social networks to collect information about a particular borrower's crop when a borrower delays the payment of her loan. Loan officers investigate about the borrower's crop to ascertain whether the borrower is facing genuine difficulties in repaying the loan or is behaving strategically. Also, as mentioned above, the funds from the agricultural loan may be diverted to bear the expenses due to social ceremonies, to start a new business, or for plain gambling/alcoholism. Because contractual enforcement of these loans is quite difficult, such diversion represents a distinct possibility. Thus, a loan officer needs to be constantly vigilant and gather information through his informal networks to ensure proper loan repayment.

From the above it is clear that much of non-verifiable information is collected using the loan officer's local networks rather than directly from the borrower. This is the principal reason why a new loan officer would be unable to instantly obtain all the non-verifiable information that the outgoing loan officer had. He cannot just summon the borrower and obtain all the information. He needs to build his own network in a village, which requires time and effort. Moreover, given the non-verifiable nature of the information, the outgoing loan officer cannot transfer this information to the new loan officer.

IV.C Loan officer incentives in Indian GOBs

Since GOBs are owned by the Government of India, employees of the bank are treated by law as "public servants".[10] For an employee of a GOB in India, the number of years spent on the job remains the most important factor that determines career progression (provided the employee's annual appraisal report shows that performance meets expectations and the employee is not under investigation for corruption). The Ministry of Finance, Government of India, decides the compensation for employees of GOBs; this compensation varies primarily based on the level of an employee in the organizational hierarchy.

Employees of GOBs in India are annually appraised for their performance on several factors that include loan origination (especially in the "priority sector" where the government mandates banks to direct lending such as agriculture, weaker sections of society et cetera), loan performance (where such loan performance can be attributed to the employee), administrative skills and leadership abilities. A composite score is provided to the employee using such appraisal of his/her performance.

Adverse performance of loans originated by a loan officer ranks as the *most important criterion* for a loan officer because of the possible penalties associated with it. Since employees of the bank are treated by law as public servants, they are subject to Government of India's anti-corruption rules. Banerjee, Cole, and Duflo (2009) describe that attribution of non-performing assets to a particular employee automatically leads to investigation, with the burden of proof on the banker to prove her innocence. Not only does the loan officer's career progression get halted, but also—given the inefficient judicial system in India—he has to run from pillar to post to prove his innocence. Therefore, as Banerjee, Cole, and Duflo (2009) describe, the "fear of prosecution for corruption hangs over every loan officer's head like a sword of Damocles."

However, when lending is based on non-verifiable information, job rotation makes it very difficult to attribute a non-performing asset to either the outgoing or the incoming loan officer. In contrast, when the loan is not affected by job rotation, loan performance can be attributed to one officer even though the loan is based on non-verifiable inputs. Therefore, the threat of investigation is quite low for *agricultural loans* affected by job rotation and quite high for agricultural loans not affected by job rotation.[11]

Thus, given the incentives faced by loan officers in GOBs in India, we expect job rotation to create free-riding in teams in our setting.

[10] See http://en.wikipedia.org/wiki/Gazetted_Officer_(India)

[11] Note, however, that if the loans were based on verifiable information, then as in Hertzberg, Liberti, and Paravisini (2010), the threat of investigation is non-trivial even in the case of loans affected by job rotation. In this case, the investigating agencies of the Indian government can attribute adverse loan performance to either the outgoing or the incoming loan officer.

V Data

We use *unique* loan account level information from a GOB in India.[12] The bank provided us data for 14 branches located in four districts in the state of Andhra Pradesh, two districts in Karnataka, and three districts in Maharashtra. The details regarding the names of districts and the location of the branches are provided in the Appendix. The loan account data starts in October 2005 and ends in May 2012.

We have data pertaining to more than 43,000 loans availed by more than 15,000 agricultural borrowers. These loans were issued by 44 different loan officers who managed the 14 branches during our sample period. We obtain information regarding the identity of the loan officer who lent a particular loan and the tenure of the loan officer in a particular branch. We have hand collected this information by verifying bank records. As described in section IV.A.1, the branch manager is the loan officer in our setting.

The transaction records provided by the bank include the date of each transaction, a short description of each transaction, transaction amount, type of transaction (debit or credit), the account balance before and after the transaction and type of balance (debit or credit). With help of the account details provided to us by the bank, we are able to infer when a loan was availed, number of days the loan was outstanding, the interest charged etc. All the loans analyzed are crop loans with a one year maturity.[13]

Dependent Variable: We define *default* as the borrower not repaying the loan by the due date of repayment. In using this definition of default, we follow RBI's guidelines for Asset Classification, Provisioning and Other Related Matters, which stipulate that a loan is considered in default if it has not been repaid by the due date of repayment.[14] Table 2 provides a brief description of all the variables used in this study.

V.A Descriptive statistics

Table 3 provides the descriptive statistics for the variables employed in our study. Loan officer tenure equals an average of 918 days, or 30 months, while the median equals 1064 days, or 35 months. Table 3 shows that our sample consists of 43,771 loans, of which 29353 loans correspond to officers that are transferred on scheduled rotation. The average loan amount equals INR 57,881 or approximately \$850 while the median loan amount equals INR 30,000 or approximately \$450. Table 3 also shows the probability of default for a loan in our sample, which consists exclusively of agricultural crop loans, is on average 63%. The median loan in our sample does not meet the payment obligations by the scheduled repayment date. Such a large rate of default may be surprising in the context

[12]The bank has a history of more than 75 years. The bank has pan India presence. It operates through more than 1000 branches.

[13]A copy of the loan agreement between the bank and borrowers of agricultural loans, which captures the various features of the loan contract, is available from the authors on request.

[14]See Section 2.1 in http://www.rbi.org.in/scripts/bs_viewmascirculardetails.aspx?id=7370#cla.

of a developed economy. However, because of the challenges related to agricultural lending described in section IV, high default rates on agricultural loans represent a key concern in developing countries such as India. In fact, concerned with the dismal performance of the agricultural sector and rising farmer suicides because of indebtedness,[15] Government of India set up a high powered committee (The Radhakrishna Committee) in 2007 to study the problem of agricultural distress and high indebtedness and suggest remedial measures. Moreover, as part of the financial budget speech delivered on February 29, 2008, the then Finance Minister of India announced an unprecedented bailout of indebted small and marginal farmers, which increases the rate of default in our sample. However, the empirical strategy we adopt, which exploits staggered transfers of loan officers all through our sample, ensures that the debt waiver scheme does not affect our results.

VI Results

VI.A Empirical strategy

Our empirical strategy relies on three critical aspects. First, we focus on agricultural crop loans, which are based primarily on non-verifiable information. Second, we utilise the bank's mandatory rotation policy to ensure that loan officer rotation is unrelated to loan officer performance. Finally, we include various fixed effects to control for unobserved factors of varying kinds.

VI.A.1 Identifying scheduled and unscheduled rotations

We start by first identifying rotation generated by the mandatory rotation policy, hereafter labelled "scheduled rotation." GOBs in India follow a uniform policy of rotating their loan officers after approximately three years.[16] Accordingly, the large GOB that provided us the data follows the same policy. A scheduled rotation is one where an officer moves out of a branch when he completes his normal tenure in a branch. Given the bank's stated policy, a loan officer normally expects to move out of a branch after completing three years. However, the loan officer cannot be moved out unless his replacement is identified and is ready to take over the responsibilities. Therefore, due to administrative reasons, loan officers get transferred on scheduled rotation a few months before or after completing 36 months.

[15] According to a UN report, more than 100,000 farmers have committed suicide since 1997, 87% of them incurring an average debt of US$835.

[16] See for example the documents detailing the rotation policies of three large public sector banks—Punjab National Bank: http://getup4change.org/rti/wp-content/uploads/2012/01/Transfer-policy-for-officers.htm; State Bank of India: http://www.sbioahc.com/business%20company_files/circulars/assn%202013/circular%20no.11.pdf; and Uco Bank: http://www.aiucbof.com/transfer_promotion.php?type=Transfer_Promotion.

In figure 1, we plot the probability of a loan officer continuing in her current branch in the $(n+1)^{th}$ month conditional on having been in the branch for n months. After 33 months, we observe a sharp discontinuity in the probability of a loan officer continuing in her current branch.[17] So, we find that the bank's rotation policy of transferring officers around three years is indeed operational on the ground. Therefore, we consider as scheduled rotations all loan officer rotations that happen after the concerned loan officer has completed at least 33 months in a branch.

Scheduled loan officer transfers are unrelated to performance. All officers are members of All India Bank Employees union, which strongly resists any move that is seen by the employees as arbitrary. Due to the potential pressure from unions, managements of GOBs stick to a uniform transfer policy. Thus, scheduled rotations are exogenous to loan officer performance. Our main tests are therefore restricted to scheduled rotations.

We now describe unscheduled rotations, which we use for some of our robustness tests. Because the Government of India only issues broad guidelines relating to rotation and promotion of loan officers, banks exercise discretion in some cases. The bank's human resources policy allows the management to transfer loan officers prematurely when faced with "administrative exigencies." Because we are not fully aware of the reasons for early rotation on a case-by-case basis, we exclude such officers from our main tests.

VI.B Probability of default

VI.B.1 Graphical evidence

As a starting point, in figure 2, we plot the probability of default on a loan as a function of the number of months spent by a loan officer in a branch at the time when that loan gets sanctioned ("officer tenure" hereafter). The figure shows the results of the following regression for different intervals of remaining tenure in the branch:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_b + \beta_k * Dummy(month \geq k) + \varepsilon_{ijkt}, \tag{1}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. $Dummy(month \geq k)$ is a dummy that takes the value of 1 for loans originated in or after month k and 0 otherwise. Here, k denotes the number of months of service of an officer in a branch. We estimate 15 separate regressions where k takes a value between 21 and 35. β_i denotes officer fixed effects that enable us to control for the effect of unobserved officer ability while β_t denotes fixed effects for each calender month. These fixed effects enable us to control for secular trends including seasonal factors. β_b denotes fixed effects at the borrower level, which help us to control for time-invariant borrower characteristics.

[17] Such operational deviations in the implementation of a 3-year mandatory rotation rule is observed are Hertzberg, Liberti, and Paravisini (2010), where regular rotation takes place after 34 months.

Therefore, we effectively compare within a borrower between loans originated before and after month k. The coefficient β_k plotted in this figure captures this difference:

$$\beta_k = \left(\overline{Y}_{\text{Loans issued in or after month } k} - \overline{Y}_{\text{Loans issued earlier}}\right)\Big|_{\text{loan officers moving on scheduled rotation}} \quad (2)$$

Figure 2 unequivocally shows that the probability of default increases monotonically as a loan officer's tenure in a branch nears completion. The before-after difference, as captured by the coefficient β_k $(k = 21, 22, ..., 35)$, remains insignificant till the 26^{th} month. The coefficient is positive and statistically significant in the 27^{th} month, which suggests that loans issued in the 27^{th} month and thereafter have a higher probability of default when compared to loans issued month till the 26^{th} month of a loan officers tenure in a branch. For all the months thereafter, i.e. 28 to 35, the coefficient is not only positive and statistically significant but also monotonically increasing in magnitude. Thus, starting from the 27^{th} month onwards, the loans originated in every month have a progressively higher probability of default.

As argued in the Introduction, all loans originated after the 27^{th} month are almost certain to be affected by job rotation. So, the monotonic increase in the probability of default in figure 2 cannot be explained by differences in screening effort (by the outgoing loan officer). Instead this monotonic increase has to stem from differences in the degree of free-riding on effort in monitoring the loans (by the outgoing loan officer).

VI.B.2 Basic tests

In our basic tests, we test for the difference in probability of default on loans issued during the end of an officer's expected tenure and loans issued earlier. Using the actual tenure for calculating the officer's expected number of months remaining in an officer's tenure could introduce forward-looking bias into these tests. Therefore, we use the expected tenure, which equals 36 months given the bank's rotation policy, to calculate the expected number of months remaining in an officer's tenure. In the online appendix, we replicate all these tests using the actual tenure and show that the results are economically stronger. As argued before, we restrict all our main tests to the group of officers who move on scheduled rotation. Having shown the results for all months from 21-36 in figure 2, here we test for the last six months, three months and one month of an officer's expected tenure. Because the maximum tenure equals 39 months in our sample and expected tenure equals 36 months, loans originated in the last six months or later are certainly affected by job rotation. We employ the following specification:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_{it} + \beta_1 * Dummy(month \geq k) + \beta \cdot X_{ij} + \varepsilon_{ijbt}, \quad (3)$$

All the terms have same meaning as in equation (1). Additionally, we include fixed effects for each (officer, month)—denoted by β_{it}—that account for time-varying officer level factors. We also include a vector of controls denoted as X_{ij} that include loan size and loan officer's tenure in the branch as on the date of loan issue. We include loan size to control for the possible correlation between the size of the loan and its performance. As we discussed in sections IV.A.1 and IV.B, agricultural lending in India is based primarily on non-verifiable information. Therefore, the loan officer has to learn about this process of acquiring non-verifiable information about the borrower. So, we include the loan officer's tenure in the branch to account for the effect of such learning on loan performance.

The results for these tests are presented in Table 4. In Columns 1 and 2, we consider last six months of an officer's expected tenure, in columns 3 and 4, we consider last three months of an officer's expected tenure and, in columns 5 and 6, we consider last one month of an officer's expected tenure. In columns 2, 4, 6, we replace the fixed effects for each (officer, month) with fixed effects for each borrower. Thus, these tests control for time-invariant borrower-level characteristics that may affect loan performance. Across columns (1)-(6) of Table 4, we notice that the coefficient estimate for β_1 is positive and statistically significant at the 1% level. We find that the probability of default on loans originated in the last six, three and one month of expected tenure are higher than that on loans originated earlier by 10%, 17% and 21% respectively. As argued in the Introduction, this difference in the economic magnitudes supports the evidence in figure 2 and suggests free-riding by both the incoming and outgoing loan officers.

VI.B.3 Tests exploiting discontinuity provided by the actual date of transfer

Results presented in Table 4 use the expected date of rotation. As explained before, we use the expected date because the loan officer is unlikely to know about the precise date of rotation a year in advance. Our conversation with the bank that give us the data highlighted to us that, depending on the circumstances of the transfer, the bank gives a notice period of 15 days to 3 months to its employees. Therefore, we hypothesize that closer to the date of rotation, a loan officer is likely to know the precise date of rotation. We use the actual date of rotation as a discontinuity to design a sharper test for the free-riding in teams that is induced by loan officer rotation. We use several windows starting from 15 days before and after rotation to 60 days before and after rotation. We test if the loans lent immediately before rotation default more when compared to loans lent immediately after. We estimate the following regression equation:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_k * Before\_Rotation\_k + \beta \cdot X_{ij} + \varepsilon_{ijkt}, \tag{4}$$

where $Y_{ijbt}, \beta_i, \beta_t$ and X_{ij} are defined as before. $Before\_Rotation\_k$ is a dummy that takes the value of 1 for loans originated within k days before actual rotation and 0 otherwise. k

refers to the before and after interval used. The sample is restricted to loans lent within an interval of k before and k days after the actual rotation date. We include officer fixed effects and year fixed effects. We cannot use month fixed effects as we have very little variation within some months given the short interval used. Similarly, we cannot use loan officer tenure as a control variable either because the construction of the tests leaves very little variation in this variable. We use loan size as a control variable.

The results are reported in Table 5. In column 1, we use an interval of 15 days before and 15 days after rotation. We increase the interval by 15 days on both sides in each of the subsequent columns. As shown in the table, the default rate of loans lent just prior to the rotation is higher by between 13.4% to 51% depending on the interval used. Given that the loans on both sides of the cut-off are lent almost at the same time, any residual concerns regarding the influence of seasonal factors or any unobserved difference between treatment and control group of loans get ameliorated substantially by these results.

VI.B.4 Robustness tests

We complete tests of our main hypothesis by identifying loans that actually straddle between two officers, i.e. loans lent by the outgoing loan officer that are due during the incoming loan officer's tenure. We compare the default rates of such loans with other loans. We estimate the following regression:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_a + \beta_{bt} + \beta_k * Straddled\_Loan + \beta_{Xij} + \varepsilon_{ijkt}, \tag{5}$$

Here the dependent variable of interest *Straddled_Loan* is a dummy variable for loans that meet the definition of straddled loans as described above, otherwise it takes the value of 0. All the terms have same meaning as in equation (1).

The results are reported in Table 6. In each column, we employ fixed effects at different levels as before. As shown in the table, the default rate of "straddled" loans is likely to be higher by 43% to 48.1%, depending on the specification used. The above result shows that deterioration in loan performance is indeed caused by loans that are *actually* handled by two loan officers. These tests may, however, suffer from possible forward-looking bias that may account for the higher economic magnitudes when compared to those obtained in table 4. Nevertheless, this result further supports our main hypothesis.[18]

[18] It is possible that the new loan officer has formal or informal access to the old loan officer. In this context, we note the following. First, based on our interviews with the bank officials and our review of official documents, we do not find any information suggesting that the current loan officer may have formal access to the old loan officer. Second, such access between the old and new officers should serve to reduce the probability of default on loans affected by job rotation, which would stack the odds against finding the positive effect of job rotation on the probability of default. We therefore believe that the effect we obtain is robust to such access.

VI.C Prior credit history of borrowers

Readers may contend that at least for repeat borrowers, default on a previous loan represents a verifiable measure of borrower quality. So, during the last few months of his tenure, if a loan officer issued loans to borrowers that have defaulted previously then his replacement can certainly dig this information and point out the same to his superiors. Anticipating such verification, a loan officer is less likely to lend to a borrower who has defaulted on a previous loan at the end of his tenure than at the beginning of his tenure. To test this thesis, we modify the specification used in equation (1) by employing prior credit history as the dependent variable. Specifically, the dependent variable is a dummy that takes the value of 1 if the previous loan lent to a borrower defaulted and zero otherwise. By construction, this test is run on the sample of repeat borrowers.

Readers may wonder why the bank would originate a loan to a borrower who has defaulted on a previous loan. However, as mentioned in section IV.A.3, agricultural loans in our sample form part of directed lending legally mandated by the Government of India. In order to meet these legal requirements, banks have to often lend agricultural loans to borrowers who have defaulted on a prior loan.

The results are presented in Table 7. The coefficient estimate for β_k is negative and statistically significant, which suggests that a loan officer is less likely to lend to a previously defaulted borrower towards the end of his tenure for fear of leaving verifiable evidence of a dubious loan.

Note that if the results obtained in Table 4 were due to differences in verifiable information, then as in Hertzberg, Liberti, and Paravisini (2010), the likelihood of default on loans affected by job rotation should be *lower, not higher* as we find. The only piece of verifiable information available about the borrower of an agricultural loan is whether or not he/she has defaulted on an earlier loan. So, the results in Table 7 further buttresses the claim that free-riding occurs in teams only when the individual contribution of each team member cannot be verified. As well, as argued in the introduction, these results highlight that our results do not stem from the GOB not caring about default on the loans originated by its loan officers.

VI.D Quantity of lending

We now examine if job rotation has any impact on the quantity of loans. Under our main hypothesis, the quantity of lending is unlikely to be affected by job rotation. This is because the quantity of loans is a verifiable measure for which only the outgoing loan officer is responsible. Therefore, as explained in section III, it is easy to fix responsibility and punish any laxity in this regard. So, we test the impact of job rotation on the quantity of loans by estimating equation (1) using the amount and number of loans as dependent variables.

The data is collapsed at branch-year-month level and the sample is restricted to officers who move on scheduled rotation. The results are reported in Table 8. In columns 1-3, the dependent variable is the amount of loan (in Rupees millions) lent by branch i in month t. In columns 4-6, the dependent variable is the number of loans lent by a branch i during month t. The independent variable of interest is a dummy variable that takes the value of 1 for last six months of an officer's tenure in columns 1 and 4, last three months of an officer's tenure in columns 2 and 5 and last one month of an officer's tenure in columns 3 and 6. We include district level macro-economic variables to control for region-specific shocks. In table 8, all the coefficients are statistically indistinguishable from 0. So, we cannot reject the hypothesis that the amount or number of loans lent towards the end of an officer's tenure are no different when compared to the amount of loans lent earlier. Thus, we do not detect any widespread and significant decline in the lending activity due to loan officer rotation.

VI.E Credit rationing

We now test whether job rotation leads to possible credit rationing. The incoming loan officer is likely to be aware of the fact that the effort exerted in screening loans lent towards the end of his predecessor's tenure is likely to be low and hence such loans are likely to be of inferior quality. Naturally, he is likely to be vary of lending to those borrowers even if they repay their loans.

We therefore investigate if the new loan officer discriminates between borrowers that were handled by the outgoing loan officer towards the end of his tenure vis-à-vis other borrowers because the new loan officer may factor in the possibility that the outgoing loan officer may not have invested optimal effort in screening loans given out during the ending months of the outgoing officer's tenure. We implement the regression equation (2) with dependent variables indicating possible credit rationing.

We report the results in Table 9. In columns 1 and 2, the dependent variable is a dummy variable that takes the value of 1 if a borrower receives a new loan within 180 days of repaying an existing loan and zero otherwise. In columns 3 and 4, the dependent variable represents the gap, in terms of days, between repayment of a loan and granting of the next loan. We test the difference between loans that straddle between two officers' tenure and other loans based on the above two parameters. We consider loans which actually move from one officer to the other and not all loans lent towards the end of the tenure because the question of rationing subsequent loans arises only if a loan is transferred to the incoming loan officer.

As evident from results in columns (1)-(2), those borrowers that took a loan during the tenure of the previous loan officer and subsequently the loan officer changed before they repaid the loan have approximately 11.6% to 16.6% less likelihood of getting a loan within 6 months of their repayment. In column 3 and 4, we find that the new loan officer takes approximately 38 to 39 more days to grant a new loan to those borrowers whose previous loan was lent by the outgoing loan officer. Please note that the gap is measured from the date of repayment of a loan. In sum, results presented in Table 9 suggest that incoming loan officers significantly curtail credit to borrowers who borrowed loans towards the end of the previous officer's tenure both by outright rejection as well as by significantly delaying the granting of new loans.

VII Alternative explanations

In this section, we consider alternative explanations for our main result.

VII.A Complimentarity between monitoring and screening ?

Suppose the screening and monitoring tasks are complementary to each other. For instance, a loan officer collects soft information about a potential borrower using his social network as in (Fisman, Paravisini, and Vig (2012)). Such information may be critical for monitoring the loan as well.Such social networks and the soft information are specific to the loan officer and are not transferable. In this case, when a loan moves from one officer to another, the incoming loan officer cannot effectively monitor the loan as he lacks the necessary soft information. Therefore, job rotation may destroy the complimentarily between screening and monitoring and thereby adversely affect loan performance.

To examine this interpretation, we examine loans that were expected to be affected by job rotation but did not get affected. This occurs primarily because of delay in loan officer rotation caused by administrative exigencies. Given the expected tenure of 36 months, all loans lent after 24 months of service by officers who served for more than 36 months in a branch fall under this category. To isolate the impact of expectation of job rotation, we drop the loans that are actually affected by rotation. Thus, the sample consists of loans that are expected to, but were not, affected by rotation and loans that were neither expected to nor were actually affected by rotation; these two groups constitute the treatment and control groups respectively.

We report the results in Table 10. We employ officer and month fixed effects in columns 1 and (officer X month) fixed effects in column 2. We also employ loan level control variables. We find that the default rate of treatment loans is higher by between 6.6% and 7.8% when compared to control loans. Since the sample for these tests was created using loans not affected by the destruction in complementarity, we can infer that our results do not stem from the same.

VII.B Disruption of borrower-loan officer relationship?

As described in section, agricultural lending in our setting is based primarily on non-verifiable information. Therefore, the relationship between the loan officer and the borrower can affect loan performance significantly. Job rotation can destroy the relationship between the loan officer and the borrower. So, it is possible that our results stem from a breakdown of the loan officer's relationship with the borrower. To investigate this concern, we examine the effect of job rotation on loan performance of borrowers having a past relationship with the loan officer and other loans. We employ the following specification:

$$\begin{aligned} Y_{ijbt} &= \beta_0 + \beta_i + \beta_t + \beta_1 \cdot Tenure\_end_{it} + \beta_2 \cdot Sameofficer_{it} \\ &\quad + \beta_3 \cdot Tenure\_end_{it} * Sameofficer_{it} + \beta_4 \cdot X + \varepsilon_{ijbt} \qquad (6) \end{aligned}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. $Tenure\_end$ takes the value of 1 for loans lent at the end of the loan officer's tenure and 0 otherwise. $Sameofficer$ is a dummy variable that takes the value of 1 if the same loan officer lends the loan under consideration as well as the previous loan to the same borrower; otherwise it takes the value 0. Thus, $Sameofficer$ captures the difference between loans to borrowers having a past relationship with the loan officer and other loans. The coefficient β_3 captures the following difference-in-difference:

$$\begin{aligned} \beta_3 &= (\overline{Y}_{\text{Rotation}} - \overline{Y}_{\text{No rotation}})\big|_{\text{loans not affected by disruption in the relationship}} \\ &\quad -(\overline{Y}_{\text{Rotation}} - \overline{Y}_{\text{No rotation}})\big|_{\text{loans affected by disruption in the relationship}} \qquad (7) \end{aligned}$$

If the results in table 4 stem from the disruption in the relationship caused by job rotation, then the effect for loans affected by the disruption in relationship must be more pronounced than the effect for loans not affected by the disruption in the relationship. In Table 11, we report the results from the above tests. The co-efficient estimate for β_3 is not always significant and flips sign based on length of end of tenure period used. This suggests that the effects of job rotation are not very different for those instances where the loan officer–borrower relationship is disrupted versus those where this relationship is not disrupted. Thus, our results in table 4 do not stem from the disruption in the relationship caused by job rotation.

Overall, we conclude that the evidence presented in tables 4 to 11 are consistent with our thesis that free-riding manifests in teams when each team member's contribution to output cannot be verified.

VII.C Borrower moral hazard?

Could our results stem from moral hazard on the part of borrowers instead of moral hazard among loan officers? Note that for borrower moral hazard due to job rotation to account for the above results, it must be the case that borrowers know when a loan officer is expected to be transferred out of the branch. Borrowers having a relationship with the loan officer are a lot more likely to know when a loan officer is expected to be transferred out of the branch when compared to borrowers not having a relationship with the loan officer. Therefore, borrower-level moral hazard due to job rotation is more likely to manifest among borrowers having a relationship with the loan officer than among among borrowers that do not have a relationship with the loan officer. However, in Table 11 we found that loan performance due to job rotation is no different for borrowers having a relationship with the loan officer when compared to borrowers that do not have a relationship with the loan officer. Thus, we conclude that borrower moral hazard is unlikely to explain our results.

VII.D Disruption of learning due to job rotation?

Could it be the case that the results stem from disruption in learning caused by job rotation? The loans issued towards the end of an outgoing officer's tenure straddle into the first few months of a new officer's tenure. Di Maggio and Van Alstyne (2012) argue that such loans perform poorly because the incoming new officer takes time to learn.

We perform two tests to rule out this possibility. First, we compare the performance of loans lent immediately prior and after the rotation. If the officer takes time to learn, then even the new loans lent by him during the beginning of his tenure are expected to default more. However, the results presented in Table 5 show that this is not the case. If our results stem from learning by the new officer, then we should not find any difference in performance of loans on either side of the cut-off. However, we find that loans lent just before rotation default more when compared to loans lent just after. In fact, in one specification, we compare the performance of loans lent during the last 15 days of outgoings officer's tenure and loans lent during the first 15 days of an incoming officer's tenure and find that loans lent just before rotation default significantly more. Note that other determinants of default such as weather, economic conditions, etc. are similar for both sets of loans.

Second, in Table 12, we compare the effect of job rotation for officers who complete their regular tenure and those who get transferred out of a branch in less than 33 months. As described before, our discussions with the bank management revealed that early rotation happen because of administrative exigencies such as need for a replacement in a branch or opening of a new branch in a nearby area and not because of performance related reasons. The key idea underlying this test is the following. An officer who gets transferred out of a branch early, say after 18 months, may not have anticipated his transfer after 18 months. Therefore, he is likely to have issued loans believing that he would have to collect the same after a year and be responsible for the performance of all his loans. Therefore, planned reduction in effort is unlikely to manifest in such cases.

Said differently, disruption in learning occurs with scheduled rotations as well as unscheduled rotations. Thus, if learning by the incoming officer drives our results, then the observed deterioration in loan performance should also manifest for the group of loan officers transferred on unscheduled rotation. We estimate the following regression:

$$\begin{aligned} Y_{ijbt} &= \beta_0 + \beta_i + \beta_t + \beta_1 \cdot Tenurend_{it} + \beta_2 \cdot Shceduled\_Rotation_{it} \\ &\quad + \beta_3 \cdot Tenurend_{it} * Shceduled\_Rotation_{it} + \beta_4 \cdot X + \varepsilon_{ijbt} \end{aligned} \tag{8}$$

The data is organized at the loan level. *Shceduled_Rotation* is a dummy variable that takes the value of 1 if the officer under consideration moves because of scheduled rotation and zero otherwise. All the terms have the same meaning as in equation (6).

In Table 12, we notice that the coefficient of interaction term between scheduled rotation and end of the tenure dummy is always positive and significant. It ranges between 25.9% when we consider straddled loans as the ones issued at the end of tenure to 50.4% when we consider last six months of tenure as tenure end. However the end of the tenure dummy, representing last six, three and one months in various specifications is mostly either negative or statistically insignificant. Please note, given that we introduce interaction terms, these dummy variables capture the differential impact of loans lent by officers who move because of unscheduled rotation. This evidence suggests that the results presented in Table 4 are not due to disruption of learning due to job rotation as in Di Maggio and Van Alstyne (2012).

VIII Conclusion

Consistent with concerns expressed by early theories of the firm (Alchian and Demsetz (1972); Holmstrom (1982)), free-riding in teams is indeed an important problem. Therefore, organisations need to use peer monitoring, social pressure, and other mechanisms to alleviate the decline in performance caused by free-riding in teams. Our study specifically pinpoints that the free-riding in teams manifests primarily when the individual contributions made by team members cannot be verified by the principal. This problem may be disproportionately more important in innovative firms, which have dominated economic activity over the last two decades. Innovative firms rely primarily on non-verifiable effort and/or actions (Aghion and Tirole (1994); Zingales (2000); Rajan and Zingales (2003)). Given the use of non-verifiable effort, measuring individual contributions poses a particularly prickly problem in innovative firms. Based on this study, we conjecture that the use of open office spaces, visible cubicles, etc. in innovative firms maybe mechanisms to offset the higher likelihood of the free riding in teams by utilising social pressure and peer monitoring. Thus, a fruitful area for further investigation would be to examine how the problem of free-riding in teams varies with the structure of information employed for decision-making in a firm.

References

Agarwal, S., and I. Ben-David (2014): "Do loan officers incentives lead to lax lending standards?," Discussion paper, National Bureau of Economic Research.

Agarwal, S., and R. Hauswald (2010): "Distance and Private Information in Lending," *The Review of Financial Studies*, 23(7).

Aghion, P., and J. Tirole (1994): "The management of innovation," *The Quarterly Journal of Economics*, pp. 1185–1209.

Alchian, A. A., and H. Demsetz (1972): "Production, information costs, and economic organization," *The American economic review*, 62(5), 777–795.

Arya, A., and B. Mittendorf (2004): "Using job rotation to extract employee information," *Journal of Law, Economics, and Organization*, 20(2), 400–414.

Banerjee, A., S. Cole, and E. Duflo (2009): "Default and Punishment: Incentives and Lending Behavior in Indian Banks," Discussion paper, Working Paper, MIT Department of Economics.

Baron, J. N., and D. M. Kreps (1999): "Consistent human resource practices," *California Management Review*, 41(3), 29–53.

Berg, T., M. Puri, and J. Rocholl (2013): "Loan officer incentives and the limits of hard information," Discussion paper, National Bureau of Economic Research.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005): "Does function follow organizational form? Evidence from the lending practices of large and small banks," *Journal of Financial economics*, 76(2), 237–269.

Berger, A. N., and G. F. Udell (2002): "Small business credit availability and relationship lending: The importance of bank organisational structure," *The Economic Journal*, 112(477), F32–F53.

Bhaumik, S. K., V. Dang, and A. M. Kutan (2011): "Implications of bank ownership for the credit channel of monetary policy transmission: Evidence from India," *Journal of Banking & Finance*, 35(9), 2418–2428.

Burgess, R., and R. Pande (2005): "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," *The American Economic Review*, 95(3), 780–795.

Burgess, R., R. Pande, and G. Wong (2005): "Banking for the poor: Evidence from India," *Journal of the European Economic Association*, 3(2-3), 268–278.

Carpenter, J., and P. H. Matthews (2009): "What norms trigger punishment?," *Experimental Economics*, 12(3), 272–288.

COLE, R. A., L. G. GOLDBERG, AND L. J. WHITE (2004): "Cookie cutter vs. character: The micro structure of small business lending by large and small banks," *Journal of financial and quantitative analysis*, 39(02), 227–251.

COLE, S. (2009): "Financial Development, Bank Ownership, and Growth: Or, Does Quantity Imply Quality?," *The Review of Economics and Statistics*, 91(1), 33–51.

COLE, S., M. KANZ, AND L. KLAPPER (2015): "Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers," *The Journal of Finance*, 70(2), 537–575.

DEYOUNG, R., D. GLENNON, AND P. NIGRO (2008): "Borrower–lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers," *Journal of Financial Intermediation*, 17(1), 113–143.

DI MAGGIO, M., AND M. VAN ALSTYNE (2012): "Information Sharing, Social Norms and Performance!," Discussion paper, Working Paper, MIT Sloan School of Management.

DOHMEN, T., AND A. FALK (2011): "Performance pay and multidimensional sorting: Productivity, preferences, and gender," *The American Economic Review*, 101(2), 556–590.

FISMAN, R., D. PARAVISINI, AND V. VIG (2012): "Cultural proximity and loan outcomes," Discussion paper, National Bureau of Economic Research.

HAMILTON, B. H., J. A. NICKERSON, AND H. OWAN (2003): "Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation," *Journal of political Economy*, 111(3), 465–497.

HERTZBERG, A., J. LIBERTI, AND D. PARAVISINI (2010): "Information and incentives inside the firm: Evidence from loan officer rotation," *The Journal of Finance*, 65(3), 795–828.

HIRAO, Y. (1993): "Task Assignmentand Agency Structures," *Journal of Economics & Management Strategy*, 2(2), 299–323.

HÖLMSTROM, B. (1979): "Moral hazard and observability," *The Bell journal of economics*, pp. 74–91.

HOLMSTROM, B. (1982): "Moral hazard in teams," *The Bell Journal of Economics*, pp. 324–340.

HOLMSTROM, B., AND P. MILGROM (1991): "Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design," *JL Econ. & Org.*, 7, 24.

ICHNIOWSKI, C., K. SHAW, AND G. PRENNUSHI (1997): "The effects of human resource management practices on productivity: A study of steel finishing lines," *The American Economic Review*, pp. 291–313.

IYER, R., AND M. PURI (2012): "Understanding Bank Runs: The Importance of Depositor-Bank Relationships and Networks," *American Economic Review*, 102(4), 1414–1445.

Jensen, M. C., and W. H. Meckling (1976): "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of financial economics*, 3(4), 305–360.

Kandel, E., and E. P. Lazear (1992): "Peer pressure and partnerships," *Journal of political Economy*, pp. 801–817.

Karmakar, K. (2008): *Microfinance in India*. SAGE Publications India.

Khwaja, A. I., and A. Mian (2005): "Do lenders favor politically connected firms? Rent provision in an emerging financial market," *The Quarterly Journal of Economics*, 120(4), 1371–1411.

Kreps, D. M. (1997): "Intrinsic motivation and extrinsic incentives," *The American Economic Review*, 87(2), 359–364.

Liberti, J. M., and A. R. Mian (2009): "Estimating the effect of hierarchies on information use," *Review of financial studies*, 22(10), 4057–4090.

Mahadevan, R., and S. Suardi (2013): "Is there a role for caste and religion in food security policy? A look at rural India," *Economic Modelling*, 31, 58–69.

Mahul, O., and N. Verma (2012): "Improving farmers' access to agricultural insurance in India," *World Bank Policy Research Working Paper*, (5987).

March, J. G. (1994): "The evolution of evolution," *Evolutionary dynamics of organizations*, pp. 39–49.

Marks, P. E., B. Babcock, A. H. Cillessen, and N. R. Crick (2013): "The Effects of Participation Rate on the Internal Reliability of Peer Nomination Measures.," *Social Development*, 22(3), 609–622.

Mas, A., and E. Moretti (2009): "Peers at work," *The American Economic Review*, 99(1), 112–145.

Petersen, M. A., and R. G. Rajan (2002): "Does distance still matter? The information revolution in small business lending," *The Journal of Finance*, 57(6), 2533–2570.

Pfeffer, J. (1996): "When it comes to best practicesWhy do smart organizations occasionally do dumb things?," *Organizational Dynamics*, 25(1), 33–44.

Prendergast, C. (2007): "The motivation and bias of bureaucrats," *The American Economic Review*, 97(1), 180–196.

Puri, M., J. Rocholl, and S. Steffen (2010): "The impact of bank relationships on default risk in consumer lending," *Available at SSRN 1572673*.

Rajan, R. G. (2009): "A hundred small steps: report of the committee on financial sector reforms," .

Rajan, R. G., and L. Zingales (2001): "The Firm as a Dedicated Hierarchy: A Theory of the Origins and Growth of Firms," *The Quarterly Journal of Economics*, 116(3), 805–851.

——— (2003): "Banks and markets: the changing character of European finance," .

Rayo, L. (2007): "Relational incentives and moral hazard in teams," *The Review of Economic Studies*, 74(3), 937–963.

Stein, J. C. (2002): "Information production and capital allocation: Decentralized versus hierarchical firms," *The Journal of Finance*, 57(5), 1891–1921.

Visaria, S. (2009): "Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India," *American Economic Journal: Applied Economics*, pp. 59–81.

Zingales, L. (2000): "In Search of New Foundations," *Journal of Finance*, 55(4), 1623–1654.

Table 2: VARIABLE DESCRIPTION

A description of all the variables used in the regressions is provided below.

Variable	Description
Default	Dummy variable; 1 when the loan has defaulted, 0 otherwise
Log (Loan Amount)	Natural log of loan amount in rupees
Straddle	Dummy variable; 1 when a loan is handled by at least two officers
Last_Six_Months	Dummy variable; 1 when a loan is originated in last 6 months expected of tenure of any loan officer, 0 otherwise
Last_Three_Months	Dummy variable; 1 when a loan is originated in last 3 months of expected tenure of any loan officer, 0 otherwise
Last_One_Month	Dummy variable; 1 when a loan is originated in last 1 month of expected tenure of any loan officer, 0 otherwise
Rationed	Dummy variable; 1 when a borrower does not obtain a new loan within 182 days of repaying the previous loan, 0 otherwise
Default in Previous Loan	Dummy variable; 1 when the borrower has defaulted on his previous loan, 0 otherwise
Next Loan within 182 Days	Dummy variable; 1 when the next loan is issued within 182 days of repayment of previous loan, 0 otherwise

Table 3: SUMMARY STATISTICS

Our sample comprise of 43,771 agricultural crop loans issued by 44 loan officers over the time period October 2005 to May 2011.

Variables	No. of Obs.	Mean	Median	Standard Deviation
Loan Officer Tenure (Days)	44	918.02	1064.00	288.11
Probability of Default	43,771	0.63	1.00	0.48
Probability of Delinquency(NPA)	43,771	0.27	0.00	0.45
Days Loan is Outstanding	43,771	605.64	515.00	466.73
Loan Amount (INR)	43,771	57881.01	30000.00	61578.12
Rainfall (cm)	43,771	10.00	9.39	3.78
Area of Rice Production ('0000 Hectares)	43,771	3557.65	3978.00	1152.52
Agricultural NPA (INR billions)	43,771	95.4	71.5	43.5
Yield of Food Grains (Kg/Hectares)	43,771	1803.36	1798.00	90.32
Direct Agricultural Lending (INR billions)	43,771	7429.0	6097.7	4664.8
Indirect Agricultural Lending (INR billions)	43,771	855.0	480.6	717.1
Total Deposits (INR billions)	43,771	69877.0	69670.0	44024.0
Literacy Rate (in percentage)	43,771	55.94	54.90	6.33
Inflation (Consumer Price Index)	43,771	145.36	134.75	26.98

Table 4: EFFECT OF MANDATORY LOAN OFFICER ROTATION ON LOAN DEFAULT

We present OLS regression results using the following specification:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's expected tenure in columns 1 and 2, last three months in columns 3 and 4, and last one month in columns 5 and 6 respectively. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			Dummy For Default			
Last Six Months	0.100***	0.114***				
	[7.745]	[5.622]				
Last Three Months			0.174***	0.143***		
			[8.469]	[4.270]		
Last One Month					0.215***	0.319***
					[4.255]	[4.373]
Loan Size	0.017***	0.121***	0.016***	0.120***	0.017***	0.121***
	[6.066]	[15.774]	[5.914]	[15.564]	[6.093]	[15.638]
Current Tenure	-0.006***	-0.005***	-0.005***	-0.003***	-0.004***	-0.003***
	[-12.331]	[-6.021]	[-11.737]	[-4.649]	[-10.412]	[-4.383]
Officer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes	No	Yes
Officer X Calender Month Fixed Effects	Yes	No	Yes	No	Yes	No
Observations	29,353	29,353	29,353	29,353	29,353	29,353
Number of Borrowers	15,489	15,489	15,489	15,489	15,489	15,489
Adjusted R-squared	0.229	0.548	0.229	0.547	0.228	0.547

Table 5: Effect of Mandatory Loan Officer Rotation on Loan Default Using Discontinuity Provided By Actual Rotation

We present OLS regression results using the following specification:

$$Y_{ijbt} \quad = \quad \beta_0 + \beta_i + \beta_t + \beta_1 * Before_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Before$ takes the value of 1 for loans lent immediately before the rotation and zero otherwise. The sample is restricted to 15 days before and after rotation in column 1, 30 days before and after rotation in column 2, 45 days before and after rotation in column 3 and 60 days before and after rotation in column 4. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

Dependent Variable	Dummy for default			
Interval	15 days	30 Days	45 Days	60 Days
Before Rotation	0.134***	0.510***	0.303***	0.282***
	[3.019]	[2.858]	[8.147]	[8.124]
Loan Size	0.008	0.012	0.020**	0.020**
	[0.457]	[0.946]	[1.965]	[2.260]
Officer Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	886	1,771	2,586	3,256
Number of Borrowers	879	1,736	2,507	3,135
Adjusted R-squared	0.163	0.172	0.185	0.180

Table 6: Effect of Mandatory Loan Officer Rotation on Loan Default Using Loans Straddling Across Two Officers

We present OLS regression results using the following specification:

$$Y_{ijbt} \quad = \quad \beta_0 + \beta_i + \beta_t + \beta_1 * Straddle_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The $Straddle_{it}$ is a dummy that takes the value of 1 for loans originated by one officer and serviced by another. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent Variable	Dummy For Default			
Straddle	0.430***	0.473***	0.430***	0.481***
	[53.843]	[55.204]	[43.118]	[33.380]
Loan Size	0.012***	0.013***	0.014***	0.108***
	[4.869]	[5.051]	[5.414]	[15.482]
Current Tenure	-0.018***	-0.021***	-0.000	-0.019***
	[-42.761]	[-41.323]	[-0.067]	[-23.586]
Officer Fixed Effect	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	No	No	Yes
Officer X Month Fixed Effects	No	Yes	Yes	No
Year Fixed Effects	No	No	Yes	No
Observations	29,351	29,351	29,351	29,351
Number of borrowers	15,489	15,489	15,489	15,489
Adjusted R-squared	0.238	0.306	0.314	0.601

Table 7: MANDATORY LOAN OFFICER ROTATION AND BORROWER CREDIT HISTORY

We present OLS regression results using the following specification:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's expected tenure in column 1 and 2, loans lent during last three months in column 3 and 4, loans lent during last one month in column 5 and 6, and for loans that are handled by more than one officers in column 7 and 8 respectively. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Dummy For Lag Default							
Last Six Months	-0.069***	-0.081***						
	[-3.323]	[-2.616]						
Last Three Months			-0.002	-0.062				
			[-0.045]	[-1.268]				
Last One Month					-0.273***	-0.218**		
					[-4.438]	[-2.125]		
Straddle							-0.051***	-0.111***
							[-3.686]	[-4.492]
Loan Size	-0.068	-0.067	-0.068	-0.055	-0.059	-0.063	-0.069	-0.069***
	[-1.318]	[-1.310]	[-1.318]	[-1.302]	[-1.292]	[-1.317]	[-1.320]	[-1.320]
Current Tenure	-0.024***	-0.041***	-0.024***	-0.041***	-0.023***	-0.041***	-0.023***	-0.040***
	[-5.718]	[-2.917]	[-5.656]	[-2.854]	[-5.425]	[-2.845]	[-5.478]	[-2.833]
Officer Fixed Effects	0.005***	0.003***	0.004***	0.002**	0.005***	0.002**	0.006***	0.005***
Calender Month Fixed Effects	[7.967]	[2.628]	[7.219]	[1.976]	[8.271]	[2.123]	[7.865]	[3.929]
Borrower Fixed Effects	0.350***	0.819***	0.367***	0.785***	0.345***	0.781***	0.331***	0.750***
Officer X Calender Month Fixed Effects	[5.672]	[5.506]	[5.949]	[5.235]	[5.606]	[5.217]	[5.269]	[5.126]
Observations	14,242	14,242	14,242	14,242	14,242	14,242	14,242	14,242
Number of Borrowers	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Adjusted R-squared	0.245	0.575	0.244	0.575	0.246	0.575	0.245	0.577

Table 8: Effect of Mandatory Loan Officer Rotation on Quantity Of Loans

We present OLS regression results using the following specification:

$$Y_{imt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{imt} is the total value of loans lent by an officer i during a month m of year t in columns 1 to 3. The variables are denominated in Rupees million in the first three columns. In the last three columns, number of loans lent at a (branch, month) level. Observations are organized at branch month level. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's expected tenure in columns 1 and 4, last three months in columns 2 and 5, and last one month in columns 3 and 6 respectively. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Loan Amount			Number Of Loans		
Last Six Months	0.22			-3.629		
	[0.513]			[-0.615]		
Last Three Months		0.27			-5.961	
		[0.458]			[-0.694]	
Last One Month			-2.65			-9.840
			[-2.621]			[-0.582]
Officer Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	612	612	612	612	612	612
Adjusted R-squared	0.192	0.172	0.193	0.221	0.112	0.123

Table 9: MANDATORY LOAN OFFICER ROTATION AND CREDIT RATIONING

We present OLS regression results using the following specification:

$$Y_{ijmt} \;=\; \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where, in columns 1 and 2, Y_{ijmt} equals 1 in if no loan is issued to a borrower within 182 days of repayment of loan j issued by officer i in calendar month m of year t. In columns 3 and 4, the dependent variable represents the gap, in terms of number of days, between repayment of a loan and disbursement of a subsequent loan. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans that are handled by more than one officers. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
VARIABLES	Rationed	Rationed	Nextgap	Nextgap
Straddle	0.116***	0.166***	37.00***	38.0***
	[15.782]	[14.605]	[8.895]	[5.446]
Loan Size	-0.010***	0.044***	4.084***	4.022
	[-3.429]	[7.314]	[2.590]	[1.353]
Officer Fixed Effect	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes
Officer X Month Fixed Effects	Yes	No	Yes	No
Observations	29,351	29,351	18,242	18,242
Number of Borrowers	15,489	15,489	9,734	9,734
Adjusted R-squared	0.200	0.680	0.0751	0.793

Table 10: JOB ROTATION AND DESTRUCTION OF COMPLEMENTARITY

We present OLS regression results using the following specification:

$$Y_{ijmt} \quad = \quad \beta_0 + \beta_i + \beta_t + \beta_1 * Treatment_Loan_{it} + \beta X + \varepsilon_{ijmt}$$

where, Y_{ijmt} equals 1 if a loan defaults and zero otherwise. The explanatory variable of interest $TreatmentLoans$ is dummy variable that takes a value of 1 for loans lent after 24th month of an officer's tenure and falling due during the tenure of the same loan officer, zero otherwise. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)
Dependent Variable	Default	
Treatment Loans	0.078***	0.066**
	[3.366]	[2.391]
Loan Size	0.020***	0.015***
	[5.892]	[4.072]
Current Tenure	-0.026***	-0.029***
	[-54.640]	[-48.275]
Officer Fixed Effect	Yes	Yes
Month Fixed Effect	Yes	Yes
Officer X Month Fixed Effect	Yes	Yes
Observations	10,861	10,861
R-squared	0.325	0.394
Number of Borrowers	6,707	6,707

Table 11: RELATIONSHIP BANKING VERSUS MANDATORY LOAN OFFICER ROTATION

We present OLS regression results using the following specification:

$$\begin{aligned} Y_{ijbt} &= \beta_0 + \beta_i + \beta_t + \beta_1 \cdot Tenurend_{it} + \beta_2 \cdot Sameofficer_{it} \\ &\quad + \beta_3 \cdot Tenurend_{it} * Sameofficer_{it} + \beta_4 \cdot X + \varepsilon_{ijtk} \end{aligned}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's tenure in columns 1 and 2, loans lent during last three months in columns 3 and 4, loans lent during last one month in columns 5 and 6 and for loans that are handled by more than one officers in columns 7 and 8 respectively. Otherwise, it takes the value of zero. $Sameofficer$ is a dummy variable that takes the value of 1 if the same loan officer lends the loan under consideration and its previous loan, otherwise it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable				Dummy For Default				
Last Six Months	0.060*	0.047						
	[1.923]	[0.674]						
Last Three Months			0.208**	0.655***				
			[2.498]	[2.859]				
Last One Month					0.344**	0.749*		
					[1.967]	[1.720]		
Stradle							0.419***	0.678***
							[14.688]	[8.518]
Sameofficer	-0.017	0.320***	-0.010	0.321***	-0.012	0.320***	-0.020*	0.348***
	[-1.411]	[13.838]	[-0.883]	[14.575]	[-1.071]	[14.488]	[-1.737]	[15.703]
Sameofficer X Last Six	0.076***	0.018						
	[2.779]	[0.264]						
Sameofficer X Last Three			0.053	-0.497**				
			[0.627]	[-2.108]				
Sameofficer X Last One					0.048	-0.267		
					[0.260]	[-0.599]		
Sameofficer X Stradle							0.064**	-0.187**
							[2.258]	[-2.315]
Loan Size	0.007	0.076***	0.005	0.077***	0.005	0.076***	0.000	0.070***
	[1.593]	[5.508]	[1.073]	[5.499]	[1.110]	[5.462]	[0.024]	[5.737]
Current Tenure	-0.012***	-0.022***	-0.011***	-0.022***	-0.011***	-0.022***	-0.023***	-0.035***
	[-15.580]	[-15.253]	[-16.915]	[-16.690]	[-16.279]	[-16.711]	[-31.558]	[-25.513]
Officer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Officer X Calender Month Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Observations	14,242	14,242	14,242	14,242	14,242	14,242	14,242	14,242
Number of Borrowers	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Adjusted R-squared	0.265	0.610	0.266	0.611	0.265	0.613	0.331	0.613

Table 12: COMPARISON BETWEEN SCHEDULED AND UNSCHEDULED ROTATION

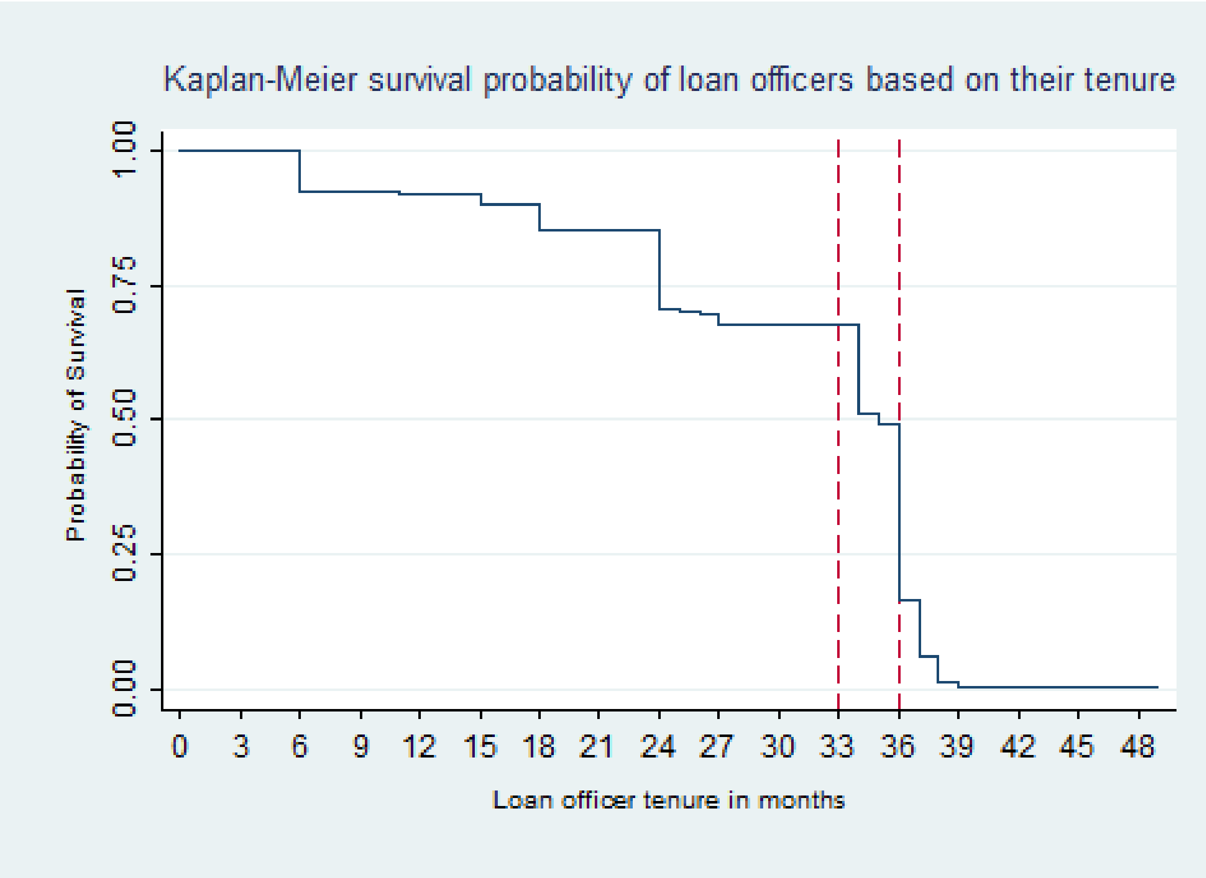
We present OLS regression results using the following specification:

$$\begin{aligned} Y_{ijbt} &= \beta_0 + \beta_i + \beta_t + \beta_1 \cdot Tenurend_{it} + \beta_2 \cdot Shceduled\_Rotation_{it} \\ &\quad + \beta_3 \cdot Tenurend_{it} * Shceduled\_Rotation_{it} + \beta_4 \cdot X + \varepsilon_{ijtk} \end{aligned}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's tenure in columns 1 and 2, loans lent during last three months of tenure in columns 3 and 4, loans lent during last one month of tenure in columns 5 and 6 and for loans that are handled by more than one officers in columns 7 and 8. Otherwise, it takes the value of zero. *Scheduled* is a dummy variable that takes the value of 1 if the officer i is transferred after completing her tenure in a branch, otherwise it takes the value of zero. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

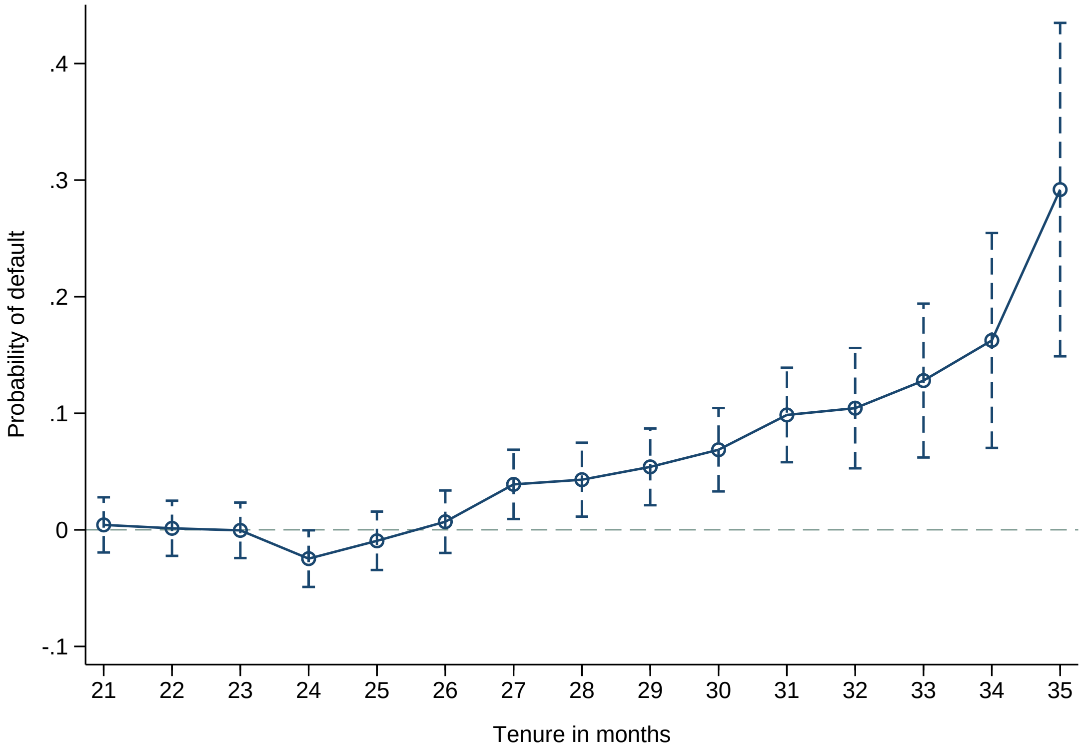
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable				Default				
Straddle	0.316***	0.291***						
	[15.402]	[19.309]						
Scheduled X Straddle	0.243***	0.259***						
	[10.989]	[16.306]						
Last_Six			-0.133***	-0.277***				
			[-7.713]	[-19.335]				
Scheduled X Last Six			0.380***	0.504***				
			[20.425]	[30.518]				
Last_Three					0.019	-0.195***		
					[0.649]	[-5.906]		
Scheduled X Last Three					0.256***	0.475***		
					[7.814]	[13.177]		
Last_One							0.095***	-0.078***
							[3.014]	[-2.733]
Scheduled X Last One							0.293***	0.490***
							[5.740]	[11.212]
Scheduled Tenure	1.033***	0.239***	0.712*	-0.002	0.685*	-0.011	0.671*	-0.026
	[4.987]	[6.166]	[1.937]	[-0.053]	[1.843]	[-0.307]	[1.852]	[-0.747]
Loan Size	0.099***	0.015***	0.122***	0.021***	0.112***	0.018***	0.113***	0.019***
	[19.235]	[7.025]	[21.406]	[9.239]	[19.278]	[7.943]	[19.652]	[8.219]
Current Tenure	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[-45.812]	[-62.310]	[-21.800]	[-26.861]	[-22.467]	[-30.884]	[-21.124]	[-29.257]
Officer Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Calender Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Officer X Month Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES
Borrower Fixed Effects	YES	NO	YES	NO	YES	NO	YES	NO
Observations	43,769	43,769	43,769	43,769	43,769	43,769	43,769	43,769
R-squared	0.612	0.585	0.563	0.623	0.555	0.643	0.552	0.512
Adjusted R-squared	0.73	0.43	0.69	0.41	0.74	0.39	0.68	0.44

Figure 1: Kaplan-Meier survival curve with Loan Officer Tenure in Months



Note: The graph shows Kaplan-Meier survival curve (also known as the Kaplan-Meier product limit estimate) against loan officers tenure (in months). The discontinuity in the graph occurs at $12_t h$ quarter which illustrates that the average loan officer gets transferred between 33 and 36 months.

Figure 2: Loan Default rates based on loan officer tenure



IX Appendix A - Location of Bank Branches

S.no	Name Of the Branch	District	State
1	Paloncha	Kothagudem	Andhra Pradesh
2	Bhadrachalam Road	Kothagudem	Andhra Pradesh
3	Mahabubnagar	Mahabub Nagar	Andhra Pradesh
4	Sattupalli	Khammam	Andhra Pradesh
5	VM Banjara	Khammam	Andhra Pradesh
6	Zaheerabad	Medak	Andhra Pradesh
7	Kohir	Medak	Andhra Pradesh
8	Medak	Medak	Andhra Pradesh
9	Peddapally	Karim Nagar	Andhra Pradesh
10	Sindhanur	Raichur	Karnataka
11	Gangavathi	Koppal	Karnataka
12	Parbhani	Parbhani	Maharashtra
13	Nanded	Nanded	Maharashtra
14	Ramtirth	Nanded	Maharashtra

X AppendixB - Additional Tables

Table A1: Effect of Mandatory Loan Officer Rotation on Loan Default Using Actual Date Of Rotation Instead Of Expected Date Of Rotation)

We present OLS regression results using the following specification:

$$Y_{ijbt} \quad = \quad \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's tenure in columns 1 and 2, last three months of tenure in columns 3 and 4 and last one month of tenure in columns 5 and 6. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Dummy For Default					
Last Six Months	0.162***	0.239***				
	[13.458]	[12.623]				
Last Three Months			0.206***	0.256***		
			[13.403]	[10.604]		
Last One Month					0.315***	0.355***
					[9.585]	[7.630]
Loan Size	0.018***	0.127***	0.016***	0.117***	0.016***	0.120***
	[6.496]	[16.523]	[5.689]	[15.072]	[5.830]	[15.548]
Current Tenure	-0.008***	-0.008***	-0.006***	-0.005***	-0.005***	-0.004***
	[-15.680]	[-9.602]	[-13.996]	[-6.525]	[-11.789]	[-5.047]
Officer Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes	No	Yes
Officer X Month Fixed Effects	Yes	No	Yes	No	Yes	No
Observations	29,351	29,351	29,351	29,351	29,351	29,351
Number of Borrowers	15,489	15,489	15,489	15,489	15,489	15,489
Adjusted R-squared	0.233	0.556	0.233	0.553	0.230	0.549

Table A2: Mandatory Loan Officer Rotation And Borrower Credit History Using Actual Date Of Rotation Instead Of Expected Date Of Rotation

We present OLS regression results using the following specification:

$$Y_{ijbt} \quad = \quad \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans that are handled by more than one officers in column 1 and 2, for loans lent in last six months of an officer's tenure in column 3 and 4, loans lent during last three months of tenure in column 5 and 6 and loans lent during last one month of tenure in column 7 and 8. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable				Dummy For Previous Loan Default				
Straddle	-0.054***	-0.113***						
	[-3.925]	[-4.588]						
Last Six Months			-0.098***	-0.098***				
			[-4.546]	[-3.310]				
Last Three Months					-0.047*	0.056*		
					[-1.883]	[1.650]		
Last One Month							-0.223***	-0.124*
	[-1.228]						[-4.962]	[-1.797]
Loan Size	-0.068		-0.068		-0.066		-0.063	
	[-1.398]		[-1.389]		[-1.347]		[-1.279]	
Current Tenure	-0.172***		-0.181***		-0.189***		-0.184***	
	[-4.196]		[-4.405]		[-4.611]		[-4.485]	
Officer Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Officer X Month Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Observations	14,240	14,240	14,240	14,240	14,240	14,240	14,240	14,240
Number of Borrowers	7,553	7,553	7,553	7,553	7,553	7,553	7,553	7,553
Adjusted R-squared	0.244	0.575	0.244	0.574	0.243	0.573	0.245	0.579

Table A3: Relationship Banking Versus Mandatory Loan Officer Rotation Using Actual Date Of Rotation Instead Of Expected Date Of Rotation

We present OLS regression results using the following specification:

$$\begin{aligned} Y_{ijbt} \;=\;& \beta_0 + \beta_i + \beta_t + \beta_1 \cdot Tenurend_{it} + \beta_2 \cdot Sameofficer_{it} \\ & + \beta_3 \cdot Tenurend_{it} * Sameofficer_{it} + \beta_4 \cdot X + \varepsilon_{ijtk} \end{aligned}$$

where Y_{ijbt} equals 1 if loan j issued to borrower b by officer i in time t defaults and zero otherwise. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's tenure in columns 1 and 2, loans lent during last three months of tenure in columns 3 and 4, loans lent during last one month of tenure in columns 5 and 6 and for loans that are handled by more than one officers in columns 7 and 8. Otherwise, it takes the value of zero. $Sameofficer$ is a dummy variable that takes the value of 1 if the same loan officer lends the loan under consideration and its previous loan, otherwise it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable				Dummy For Default				
Straddle	0.419***	0.675***						
	[14.678]	[8.494]						
Last Six Months			0.172***	0.194**				
			[4.930]	[2.414]				
Last Three Months					0.404***	0.817***		
					[4.564]	[3.237]		
Last One Month							0.524***	0.844***
							[3.726]	[2.51]
Sameofficer	-0.018	0.351***	-0.005	0.339***	-0.002	0.337***	-0.006	0.331***
	[-1.558]	[15.849]	[-0.426]	[14.931]	[-0.157]	[15.438]	[-0.555]	[14.98]
Sameofficer X Straddle	0.064**	-0.183**						
	[2.246]	[-2.276]						
Sameofficer * Last Six			0.054*	0.000				
			[1.677]	[0.005]				
Sameofficer X Last Three					-0.152*	-0.587**		
					[-1.705]	[-2.297]		
Sameofficer X Last One							-0.085	-0.443
							[-0.588]	[-1.29]
Loan Size	-0.000	0.068***	0.007	0.078***	0.003	0.074***	0.003	0.074***
	[-0.030]	[5.537]	[1.571]	[5.718]	[0.768]	[5.185]	[0.670]	[5.29]
Current Tenure	-0.023***	-0.035***	-0.014***	-0.024***	-0.012***	-0.023***	-0.012***	-0.023***
	[-31.677]	[-25.585]	[-18.352]	[-17.594]	[-18.113]	[-17.788]	[-17.638]	[-17.13]
Officer Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calender Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Officer X Month Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Observations	14,240	14,240	14,240	14,240	14,240	14,240	14,240	14,240
Number of Borrowers	7,553	7,553	7,553	7,553	7,553	7,553	7,553	7,553
Adjusted R-squared	0.330	0.659	0.269	0.614	0.269	0.614	0.269	0.616

Table A4: Mandatory Loan Officer Rotation And Quantity Of Loans: Using Actual Date Of Rotation Instead Of Expected Date Of Rotation

We present OLS regression results using the following specification:

$$Y_{imt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Tenureend_{it} + \beta X + \varepsilon_{ijmt}$$

where Y_{imt} is the total value of loans lent by a branch i during a month m of year t in columns 1 to 3. The variables are denominated in Rupees million in the first three columns. In the last three columns, number of loans lent at a (branch, month) level. Observations are organized at branch month level. The explanatory variable of interest $Tenureend$ takes the value of 1 for loans lent in last six months of an officer's tenure in columns 1 and 4, last three months of tenure in columns 2 and 5 and last one month of tenure in columns 3 and 6. Otherwise, it takes the value of zero. Officers experiencing scheduled rotation (i.e. tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Loan Amount			Number of Loans		
Last Six Months	-10.455*			-12.498		
	[-1.930]			[-1.568]		
Last Three Months		0.418			-2.985	
		[0.697]			[-0.350]	
Last One Month			-1.863*			-24.986
			[-1.935]			[-1.449]
Rainfall	0.007	0.021	0.017	0.296	0.381	0.409
	[0.136]	[0.426]	[0.383]	[0.226]	[0.299]	[0.332]
Drought	0.107	0.182	0.255	-0.009	-0.007	-0.007
	[0.207]	[0.353]	[0.515]	[-0.903]	[-0.697]	[-0.677]
NPA	-0.066	0.025	0.027	0.002	0.003	0.003
	[-0.202]	[0.087]	[0.096]	[0.563]	[0.631]	[0.616]
Agri_Lending	0.009*	0.003	0.004	-0.058	-0.074*	-0.073*
	[1.917]	[1.111]	[1.562]	[-1.267]	[-1.755]	[-1.793]
Inflation	-0.084***	-0.053***	-0.689**	0.133	0.085	0.026
	[-2.845]	[-1.318]	[-2.161]	[0.268]	[0.162]	[0.051]
Literacy	1.559***	1.360***	1.426***	25.464***	25.457***	24.883***
	[3.249]	[2.889]	[3.101]	[3.391]	[3.375]	[3.265]
Yield	-0.060***	-0.047**	-0.465**	-0.581*	-0.572*	-0.546
	[-2.675]	[-2.392]	[-2.400]	[-1.660]	[-1.646]	[-1.560]
Officer Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	611	611	611	611	611	611
Adjusted R-squared	0.45	0.37	0.38	0.39	0.42	0.41