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Costs of Job Rotation: Evidence from Mandatory Loan Officer Rotation

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Abstract. Job rotation inside an organization creates two conflicting effects. It disciplines agents by creating the fear that their successors may discover and report their hidden information. Thus, the agent takes actions that align with the principal's objective. However, job rotation can create a moral hazard problem. If information is soft and therefore, non-verifiable, the principal cannot attribute blame to the agent or the successor. Agents shirk, thereby hurting performance. Thus, the importance of disciplining versus moral hazard effects depends on the availability of hard information. Using unique loan-level data, we show that job rotation hinders performance when the information is soft.

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1. Introduction

In many economic settings, agents are required to perform tasks and also report about the quality of performance (Keys et al. 2010, Toffel and Short 2011, Agarwal and Ben-David 2014, Piskorski et al. 2015). When the underlying effort and the outcomes are independently verifiable, the threat of such verification is likely to deter suboptimal behavior. Therefore, learning about the actual state of affairs of the jobs within is one important motive for organizations to practice job rotation (Ortega 2001, Hertzberg et al. 2010). However, when the underlying information is not verifiable (Petersen 2004; Agarwal and Hauswald 2008, 2010; DeYoung et al. 2008; Keys et al. 2010; Di Maggio and Van Alstyne 2012), a predictable and rule-based job rotation could impose costs in the form of shirking on jobs that are expected to outlive an agent's tenure. To the best of our knowledge, the costs of job rotation in an environment where the underlying information is soft have not received sufficient scholarly attention.[1]

The cost that we highlight is important because decision making inside firms involves not only hard information, which can be hidden but is verifiable (Tirole 1986, 1992; Laffont and Tirole 1991a, b, 1992a, b), but also, soft information (Petersen 2004, Agarwal and Hauswald 2010, Agarwal and Ben-David 2018). In general, soft information is involved in decision making whenever decisions utilize judgment, intuition, or experience. A wide range of professionals, including doctors, lawyers, business executives, judges, bureaucrats, and lenders, extensively uses soft information (Aghion and Tirole 1994; Rajan and Zingales 1998, 2001; Agarwal and Hauswald 2010).

Given the use of hard and soft information for decision making, job rotation inside an organization creates *two conflicting effects*. On the one hand, job rotation disciplines agents. As Hertzberg et al. (2010) highlight, job rotation creates the possibility that an agent's successor may discover and report information that the agent hides. Successors are likely to exert effort on incomplete jobs that they are newly assigned to if the management, because of availability of hard information, can independently verify their efforts concerning the straddled jobs. Career concerns then inhibit the agents' tendency to shirk their job and motivate them to take actions that align with the principal's objectives. In this way, job rotation is beneficial to the firm.

However, there is an opposite consequence of job rotation when the agent's actions do not generate hard information: moral hazard in teams a la Holmstrom (1982). Job rotation creates a situation where two agents—incumbent and successor—need to be incentivized simultaneously. This situation engenders a moral hazard. First, knowing that the outcome of their activities will be revealed only during the tenure of their successor, incumbents will shirk their responsibilities because it will be hard to attribute to them the negative outcome of their actions. Second, successors may shirk their responsibility because the principal cannot attribute the responsibility to them when hard information is unavailable. Thus, both will shirk their responsibility, thereby hurting performance.

These two conflicting effects of job rotation are always at play, and their relative importance depends on the availability of hard information. The disciplining effect of job rotation can only manifest itself if the agent's successor can discover and report (to the principal) information that the agent may hide. Such reporting requires that the information be hard: that is, it can be hidden but is verifiable. Thus, the less hard information that is available, the greater the cost is relative to the benefit. Hertzberg et al. (2010) show using detailed internal records from a multinational bank in Argentina that job rotation improves performance. In their setting, loan officers make loans to small and midsize corporations, where soft, unverifiable information is supplemented by (verifiable) loan documentation. We analyze the consequences of job rotation in an environment where agents leave very little hard information that explains their actions: crop loans provided by an Indian bank to farmers who do not possess any financial reports or documentation of their activities and who do not pay taxes. Here, the information on which the loan is based is primarily soft. In this setting, we show that mandatory job rotation reduces the performance of crop loans when the loan maturity is beyond the agent's tenure on the job.

We provide this evidence using *unique* data provided to us by a public sector bank in India on (i) agricultural crop loans and (ii) the loan officers who give these loans. We use agricultural crop loans for two reasons. First, agricultural lending in a developing country like India is based primarily on soft information. Second, because agricultural crop loans have a fixed maturity of one year, a loan officer (and an econometrician) can clearly identify loans that would straddle her tenure and that of her replacement.

For identification, we follow Hertzberg et al. (2010) and exploit the mandatory rotation policy used by the bank. As part of this policy, the bank rotates its loan officers after the officer has completed three years in a particular branch. Thus, in our setting, the rotation of loan officers is exogenous to their performance.

The sample of agricultural crop loans in India provides a clean empirical setting. Hertzberg et al. (2010) study the effect of job rotation on term loans to small and midsize corporations, which involve interim interest payments. Moreover, soft and unverifiable information on the borrower is supplemented by (verifiable) loan documentation. Interim interest payments and (verifiable) loan documentation represent verifiable signals that an incoming loan officer can use to ferret out shirking. In contrast, agricultural crop loans in our setting are zero-coupon loans that do not require any interim payments. All loans have a maturity period of 12 months. Nonpayment of the full amount due on or before the due date is considered as default. More so, crop loans are provided by Indian banks to farmers who do not document their activities, do not possess any financial reports, and also, do not pay taxes. The only piece of credible hard information available is information about loan repayment of past loans with the bank.

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

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. Starting from the 27th month, we find that the loans originated in every month have a progressively higher probability of default than loans originated before. We then identify and examine loans that straddle between officer tenures (henceforth, straddled loans) owing to scheduled mandatory rotation. We find that the default rate of such loans is significantly higher than other loans that do not straddle.

In our subsequent tests, we compare the probability of default on loans originated in the last six, three, and one month of a loan officer's expected tenure vis-à-vis loans originated earlier. As argued, these loans are certainly affected by job rotation. This identification strategy allows us to avoid the possible look-ahead bias arising from considering actually straddled cases. We find that the probabilities of default on loans originated in the last six, three, and one month of expected tenure are higher than those on loans originated earlier by 10%, 18%, and 22%, respectively. As argued, the difference in the economic magnitudes further supports shirking by both the incoming and outgoing loan officers.

For repeat borrowers, prior default represents a verifiable piece of information that the bank possesses. Thus, 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 who have defaulted on their previous loan at the end of her tenure compared with the beginning of her 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 et al. (2010).[2]

We then analyze other possible explanations other than shirking. The readers may contend that our results are owing to (i) the new officer discontinuing the evergreening operations of the outgoing officer, (ii) time taken for learning by the incoming loan officer, (iii) destruction of the loan officer–borrower relationship because of job rotation (Drexler and Schoar 2014), and (iv) disruption of complementarity between screening and monitoring.

To test the explanations, we first examine loans that were expected to be—but were not—affected by rotation and compare them with loans that were neither expected to nor actually affected by rotation. We find relative underperformance of loans belonging to the first category, which suggests that the difference in screening effort plays a role in explaining our results. It seems that the outgoing officer shirks with respect to loans that are expected to move under normal circumstances. The result is inconsistent with evergreening, learning, destruction of the relationship, and loss of complementarity explanations. In the case of evergreening, the outgoing officer would have further evergreened such loans because the entire purpose of evergreening is to avoid recognition of default. The question of learning by new officers or destruction of loan officer borrower relationship does not arise because the treated loans here are only expected to move but did not actually move. Finally, in this sample, complementarity between the tasks, if any, is preserved because the same officer handles both types of loans throughout her tenure.

Then, we contrast the effect of job rotation on (i) loans originated by a loan officer who already had a prior relationship with the borrower and (ii) loans where the borrower did not have a prior relationship. We find no difference in the effect of job rotation on these two samples. The result is inconsistent with the hypothesis that our results are owing to the breakdown of the borrower-officer relationship as in Drexler and Schoar (2014).

Additionally, we study the effect of job rotation on loans that are affected by *unscheduled* rotation: that is, loans originated by officers that move before completing their scheduled tenure in their branch. Sometimes, loan officers are rotated early because of administrative exigencies. We do not have complete details about the kind of administrative exigencies that lead to premature rotations. Therefore, the evidence presented here is, at best, suggestive. We find that, within the sample of straddled loans, the loans that straddle from officers that complete their tenure default more. The result supports the shirking hypothesis because the chance of planned shirking is higher in case of scheduled rotations. The result is inconsistent with the learning hypothesis because the new loan officer's learning is unlikely to be related to the tenure of the outgoing officer.

The evidence described so far indicates that the outgoing officer shirks in screening. As noted before, in the absence of credible verification, there is reason to believe that even the incoming officer is likely to shirk in monitoring. We provide some suggestive evidence in this regard. We show that even within straddled loans, on which the outgoing officer's level of screening effort is likely to be similar, the default rate increases with the length of time that these loans are handled by the incoming officer. However, because of the presence of soft information, neither the bank management nor an econometrician can precisely estimate the relative contribution of poor screening and poor monitoring to the incremental defaults of loans impacted by job rotation.

Our study is related to the organizational economics literature on job rotation (Hirao 1993, Arya and Mittendorf 2004, Hertzberg et al. 2010, Di Maggio and Van Alstyne 2012). We highlight free riding when job rotation occurs in an environment where decision making is based on nonverifiable information. We also contribute to the financial intermediation literature that (i) examines the effect of incentives in financial intermediation (Agarwal and Hauswald 2010, Berg et al. 2013, Agarwal and Ben-David 2014, Cole et al. 2015, Tantri 2018b) and (ii) studies the use of nonverifiable and verifiable information in bank lending (Rajan and Zingales 2001, Berger and Udell 2002, Stein 2002, Berger et al. 2005, DeYoung et al. 2008, Liberti and Mian 2009, Agarwal and Hauswald 2010, Puri et al. 2010, Drexler and Schoar 2014). We highlight the perverse incentives created by job rotation when lending is based on nonverifiable information.

2. Theoretical Background

We describe the theoretical arguments that allow us to test the cost of job rotation. To understand the arguments clearly, consider a principal-agent relationship, where a bank is the principal and loan officers are the agents. The handling of a loan from the screening to recovery is a job, and screening and monitoring are two key tasks.

Let us start with a setting where the effort exerted by an agent or multiple agents can be clearly verified by the principal or another agent of the principal. Moreover, based on the historical relationship or theory, the principal knows the relative contribution of the two tasks (screening and monitoring) in the successful completion of the job. In this environment, job rotation acts as a disciplining device. An incoming officer will be able to credibly verify the effort exerted by the outgoing officer and report to the management. The management can then incentivize both officers optimally based on their effort level. The outgoing officers can be assessed based on their effort expended on screening and initial monitoring until job rotation, and the incoming officers can be assessed based on their effort in monitoring after the rotation and eventual loan recovery. The outgoing officers can be held accountable, even in cases where their effort level gets revealed after an interval because the officers, in most cases, remain within the organization. That is, the management can use job rotation as a tool to verify effort levels of officers cost effectively. Alternatives, such as a detailed audit, are likely to be more expensive. Anticipating verification by the incoming officer, the incumbent is likely to exert more effort as rotation becomes imminent. Therefore, job rotation plays a disciplining role. The description broadly applies to the setting studied by Hertzberg et al. (2010), where the incoming officer can verify the effort level of the outgoing officer.

It is crucial to note that the kind of verification described is possible only if decision making is primarily based on hard information. It is relatively easy to verify whether a particular accounting ratio, say interest coverage ratio, was considered in arriving at an internal rating for a borrower or whether an anomaly in a document, such as a mismatch with the details provided by another related but more credible document, was considered. However, in many cases, such hard information may not be available, and even where available, it may not be entirely reliable. In such cases, an officer will have to depend on soft information (Agarwal and Hauswald 2010). An example is a situation where an officer assesses whether a particular borrower is honest and has a good social network that helps in periods of distress. Whether this information is correct cannot be easily verified by the management. Furthermore, even the process used by the officers to collect information cannot be reliably verified to account for their effort.

Given this background, consider a second setting where a loan officer's decision making is mostly dependent on soft information. In this situation, it is extremely hard for the management or a new officer to verify the effort exerted by an officer in screening and monitoring. It is crucial to note that even monitoring will require soft information. Officers must update their information about a borrower to devise an effective recovery strategy. A borrower's views on strategic default may change with time if strategic default becomes socially acceptable because of some shock (Guiso et al. 2013, Towe and Lawley 2013, Tantri 2018a). Only an officer who has a good social network in the field will be able to understand these trends in time and devise an effective loan recovery strategy. For example, restructuring a loan in case of a strategic default may not be appropriate, whereas doing so when a borrower suffers from a temporary liquidity shock may lead to better outcomes for the bank.

A job rotation policy in an environment dominated by soft information is likely to lead to the shirking of responsibilities relating to loans that straddle between officer tenures, by both the incoming and outgoing officers because neither screening nor monitoring efforts can be reliably verified. Therefore, there is no reliable basis for apportioning a reward or punishment for the final outcome. Loans that are handled by a single officer are unlikely to suffer from this problem, even when decision making is based on soft information, because the management can easily reward the officer based on the final outcome. The division between screening and monitoring does not matter in this case.

Job rotation in our setting induces two more complications. First, the loans that we study are bullet loans, where the entire loan outstanding with interest is required to be repaid at maturity. Unlike in Hertzberg et al. (2010), there are no intermediate signals coming from monthly repayments. Thus, our setting does not correspond to the multitasking setup studied by Holmstrom and Milgrom (1991) because screening and monitoring do not produce measurable outputs by themselves.

Second, the relative contribution of screening and monitoring could change with time. As noted before, when hit with a shock that induces strategic default as in Guiso et al. (2013), Towe and Lawley (2013), and Tantri (2018a), the relative importance of monitoring in contributing to final loan recovery may increase midway during the life of a loan. For new cases, screening may become more important in an environment with strategic default. This difficulty in apportioning credit between monitoring and screening further complicates management's ability to incentivize officers on loans that are handled by more than one officer.

It is important to ask whether, at least for repeat borrowers, hard information in the form of performance of past loans with the bank curbs opportunistic shirking. The incoming officer or the management could potentially verify whether the outgoing officer lent disproportionately more to borrowers with a dubious track record. Such a possibility should work as a deterrent against differential selection based on past performance. Suppose that the outgoing officer ensures that, with respect to hard information, the portfolio that straddles is similar to the rest of her remaining loan portfolio; then, there is little that the incoming officer can detect.

It is crucial to note that two borrowers having similar past loan repayment records may differ significantly in terms of soft information and hence, likely future performance. Keys et al. (2010) show that, even in a developed country setting, borrowers having similar credit histories perform differently because of the difference in soft information. Past performance with one bank is a subset of the overall credit information, and hence, there is a higher scope for considering soft information in our setting, even for repeat borrowers.

Consider two borrowers, A and B, who have never defaulted in the past. Although they are similar in terms of past track records, they may significantly differ in terms of soft information. For instance, it is possible (i) that A has an excellent social and family network to support her and B does not; (ii) that A plans to continue her regular farm operation, whereas B plans to engage in some kind of risk-shifting behavior by either investing in risky crops or moving out of farming; (iii) that A has a higher need for repeated loans from the bank because she plans to invest more compared with B; (iv) that A is planning to spend on some personal ceremonies, whereas B has no such plans; and (v) that A's nonagricultural income increased last year, whereas B's nonagricultural income decreased. In fact, it is also possible that a borrower with a clean track record is a worse credit compared with a borrower with not so good past record with a bank because of unobserved time-varying shocks induced by nature. It is almost impossible for the incoming loan officer to assess whether the outgoing officer has considered such important soft information. Therefore, even in repeat cases, the outgoing officers are likely to shirk with respect to the collection of soft information.

3. Institutional Background

3.1. Loan Features

The sample of loans consists of crop loans issued to farmers located in three large states of India. All of the loans have a fixed tenure of one year. In addition, all of the loans in the portfolio are bullet loans, where the total outstanding amount is required to be paid in one installment on or before the due date. No intermediate repayments are stipulated.

Typically, land and standing crops are used as collateral for these loans. Poorly delineated property rights over land exacerbate the problem by making it difficult for the bank to foreclose land presented as collateral. Moreover, foreclosing a farmer's land or crop is an extremely politically sensitive issue because local politicians, cutting across party lines, intervene on behalf of farmers.[3] Effectively, farmers in India do not face the threat of their collateral being taken over by their lenders, which encourages strategic default.

Given the weak loan enforcement mechanism, the loan officers generally adopt two approaches for loan recovery. (i) As shown by Breza (2012), loan officers use the threat of denial of a new and plausibly, larger loan. (ii) Loan officers also use their social connections (Fisman et al. 2017).

3.2. Loan Performance

A loan is considered to be in default if it is not fully repaid by the due date. Note that default only means that the borrower has missed the payment to be made on the due date. The loan is not considered a non-performing asset (NPA), and it is not written off immediately after default. A loan is considered an NPA when it is in default for at least two crop seasons. Generally, the underlying crop in our case is rice, and its crop season is six months (Mukherjee et al. 2018). In this case, a loan will be considered an NPA if it remains in default for over a year. The loan portfolio has an average default rate of 63%. However, the NPA rate is 27%. As noted in Section 3.1, slow-moving contract enforcement mechanisms and political interference in lending contribute to higher default rates.

3.3 Importance of Nonverifiable (Private) Information

Agricultural lending in a developing country like India is based primarily on nonverifiable private information. First, apart from routine information, such as names and addresses among others, the loan officer does not have access to any other relevant and verifiable information. Because agricultural income in India is exempt from income tax,[4] small farmers who have no other source of income other than agricultural income do not file income tax returns. Additionally, there is not an independent audit of the farmers' income. Given that nearly 44.1% of small farmers in India have little education (Mahadevan and Suardi 2013), proper annual records of production are not maintained by them. Moreover, no publicly available credit history exists for borrowers of small agricultural loans in India.

The farms in our sample are quite small; the farmers have landholding of fewer than two hectares. Nearly 65% of small farmers depend on rain-fed irrigation (Mahadevan and Suardi 2013). More so, 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 crop insurance. This situation 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 the geographical proximity to the borrower and the hierarchical distance (that is, 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) determines crucially the use of verifiable versus nonverifiable information for lending (Petersen and Rajan 2002, Berger et al. 2005, Liberti and Mian 2009, and Agarwal and Hauswald 2010 among others). Specifically, ceteris paribus, the greater the geographical distance or the hierarchical distance, the greater the reliance on verifiable information because of the ease with which verifiable information can be transmitted geographically or across organizational layers and interpreted correctly. All of the bank branches that we study are rural branches that have only one loan officer—the branch manager—who is assisted by four to five clerical staff members. We observed during the data collection exercise that the branch manager meets all of the borrowers personally before approving crop loans. The branch manager is located geographically proximate to the borrowers and regularly interacts with them. Moreover, as part of the policy set by the bank, loans below the size of Indian rupees (INR) 0.65 million can be sanctioned by the branch manager. Because the size of the agricultural crop loans in our sample is much smaller (approximately INR 30,000), the loan officer has the authority to sanction these small-sized agricultural crop loans without having to seek the permission of a higher-ranked officer. Therefore, the scope for using soft information is very high.

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).[5] The loan officer's interactions with the borrowers are only through the loan account and related transactions. As a result, unlike in Puri et al. (2010), loan officers cannot utilize information from savings or checking accounts to obtain verifiable information about the borrower.[6]

3.4. Loan Officer Incentives

As noted in Section 1, we study the loans issued by loan officers of a listed bank that is also partially owned by the government. Here, we briefly describe the formal incentive structure applicable to loan officers. The number of years spent on the job remains the most important factor that determines career progression. The compensation varies primarily based on the level of an employee in the organizational hierarchy. Loan officers are annually appraised for their performance on several factors that include loan origination, loan performance (where such loan performance can be attributed to the employee), administrative skills, and leadership abilities. A composite score is provided to employees using such an appraisal of their performance. However, as described in Section 2, the use of soft information makes it extremely hard to assign responsibility with respect to loans that are not fully handled by an officer.

3.5. Need for Monitoring

From the description of the economic setting, it is clear that the loan officer will have to use soft information for effective screening. However, the need for, technology of, and use of monitoring need some explanation. Unlike a conventional business loan setup, the loans here are bullet loans, which deprive the officers of intermediate signals. There are no audited documents to assess the recent economic situation of the borrowers. Although the lack of documents and bullet loans structure may change the technology of monitoring, they do not alleviate the need for monitoring. Even for bullet loans, a loan officer is required to make a number of important decisions before and at the time of repayment. These decisions include the decision to intervene midway through the loan and counsel the borrower about consequences of moral hazard on future loans, identifying and addressing risk-shifting behavior in time, the method of recovery to be adopted, the formal or informal restructuring methods to be adopted, offering additional loans when the opportunity or need arises, and tapping social network in advance to avert strategic default among others. These decisions require up to date information about the borrower. The officer needs to have some idea about the latest economic situation of the borrower: her personal and family status in terms of health, planned ceremonies, migration decision, and others; the state of affairs of the operations of the farmer; and the availability of inputs, such as water, fertilizer, etc. An officer who collects information at the time of screening but does not monitor the loans is unlikely to be effective even in this setting.

4. Data

We use *unique* loan account-level information from a large bank in India. The bank provided 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 the districts and the location of the branches are provided in the online appendix. We provide further information relating to sample construction in Table 1. The loan account data start in October 2005 and end in May 2012.

Table 1. Sample Construction

Category	Value
Sample period	October 2005 to May 2012
Number of states	3
Number of branches	14
Number of officers	44
Number of loans in the sample	43,771
Number of loans lent by officers moving on scheduled rotation	29,353
Number of loans without a predecessor loan within the same account	19,072
Number of loans with a predecessor loan within the same account	24,699
Number of same officer loans	10,680
Number of different officer loans	14,019

Notes. In this table, we report the details about the construction of our sample. Same officer loans refer to loans in which the same officer issued the loan and the immediately preceding loan. Different officer loans refer to loans where different officers issued the loan and the immediately preceding loan.

We have data pertaining to more than 43,000 loans availed by more than 15,000 borrowers. Nearly 25,000 loans are those where the officer has dealt with the borrower more than once, and the remaining loans are first-time loans. Within the repeat loans, close to 10,000 loans are those where the same officer issued more than one loan to a borrower. These loans were issued by 44 different loan officers who managed the 14 branches during our sample period. Officers who move on scheduled rotation issued 29,353 loans. We obtain information regarding the identity of the loan officer who issued a particular loan and the tenure of the loan officer in a specific branch. We hand collected this information by verifying bank records. As described in Section 3.1, the branch manager is the loan officer in our setting. The bank branches were selected through a draw of lots. Within each branch, we collected information on all crop loans issued by a branch and the tenure of all loan officers who served in these branches during our sample period. A detailed note presented in Section IV of the online appendix describes the sample selection procedure.

The transaction records provided by the bank include the date of each transaction, a short description of each transaction, the transaction amount, the type of transaction (debit or credit), the account balance before and after the transaction, and the type of balance (debit or credit). Given the account details provided to us by the bank, we can infer when a loan was availed and the number of days that the loan was outstanding among others. All of the loans analyzed are crop loans with a one-year maturity.

Table 2 provides descriptive statistics for the variables used in our study. Loan officer tenure equals an average of 918 days or 30 months, whereas the median equals 1,064 days or 35 months. The average loan amount equals INR 57,881 or approximately $850, whereas the median loan amount equals INR 30,000 or approximately $450. Table 2 also shows that the probability of default for a loan in our sample, which consists exclusively of agricultural crop loans, is, on average, 63%. However, as noted in Section 3.2, the NPA rate is much lower at 27%. We use default as a measure of loan performance because it triggers provisioning and shows the first signs of trouble.

5. Results

5.1. Empirical Strategy

5.1.1. Identifying Scheduled and Unscheduled Rotations.

We start by first identifying rotations generated by the mandatory rotation policy, which is, hereafter, labeled "scheduled rotation." The bank follows a uniform policy of rotating its loan officers after approximately three years.[7] A scheduled rotation is one

Table 2. Summary Statistics

Variables	Mean	Median	Standard deviation
Loan Officer Tenure (Days)	918.02	1,064.00	288.11
Probability of Default	0.63	1.00	0.48
Probability of Delinquency (NPA)	0.27	0.00	0.45
Days Loan is Outstanding	605.64	515.00	466.73
Loan Amount (Rupees)	57,881.01	30,000.00	61,578.12

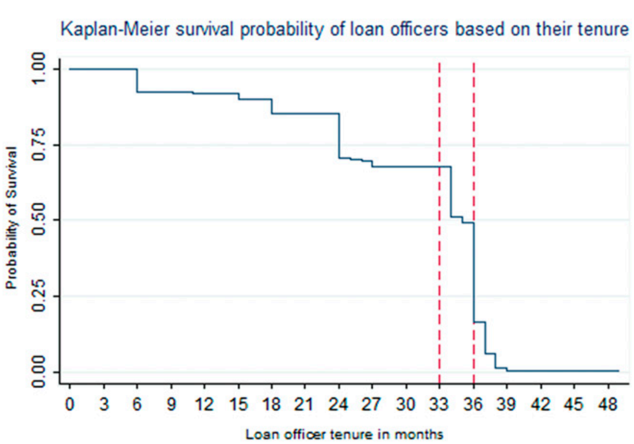
Note. In this table, we report key summary statistics.

where an officer moves out of a branch after completing her 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 a replacement is identified and ready to take over the responsibilities. Therefore, because of administrative reasons, loan officers get transferred on scheduled rotation a few months before or after completing 36 months.

In Figure 1, we plot the probability of an officer continuing in her current branch in the $(n+1)^{\text{th}}$ month conditional on having been in the branch for n months. After 33 months, we observe a sharp discontinuity in the probability of an officer continuing in her current branch.[8] Thus, we find that the bank's rotation policy of transferring officers around three years is, indeed, operational. Therefore, we consider all rotations that happen after the concerned officer has completed at least 33 months in a branch as scheduled rotations. It is clear from the discussion that scheduled loan officer transfers are unrelated to performance and that are only determined by the time spent by an officer in a branch. In this case, officers can anticipate, with a reasonably high level of confidence, whether a loan will come due during their tenure and plan their effort level accordingly.

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 most of our tests.

Figure 1. (Color online) Kaplan–Meier Survival Curve with Loan Officer Tenure in Months



Notes. The graph shows the 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 the 12^{th} quarter, which illustrates that the average loan officer gets transferred between 33 and 36 months.

5.2. Probability of Default

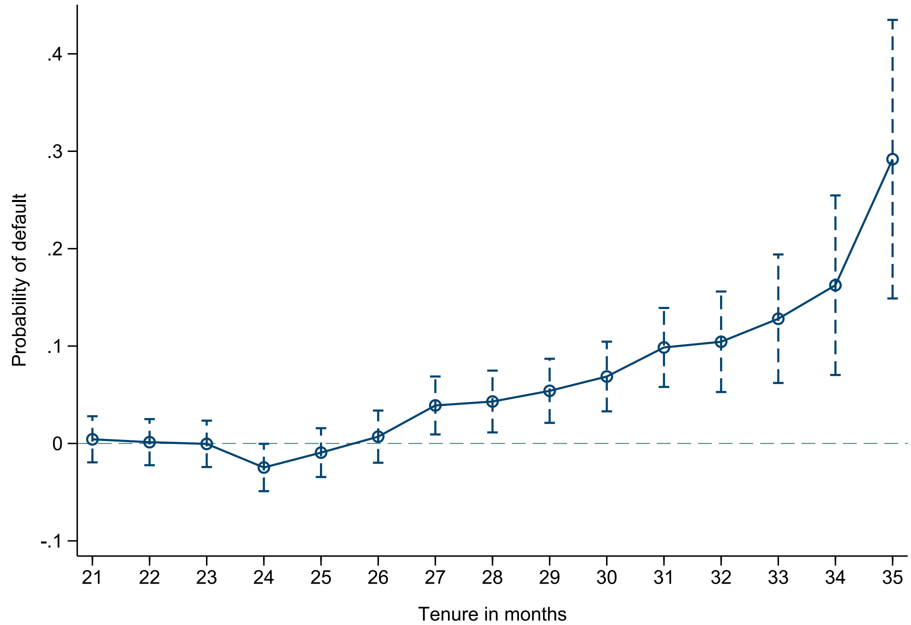
5.2.1. Graphical Evidence. In Figure 2, we plot the probability of default on loans as a function of the number of months spent by a loan officer in a branch at the time when that loan gets sanctioned ("officer tenure" hereafter). The figure shows the results of the following regression for different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

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_b + \beta_k \times Dummy(month \geq k)_{ijbt} + \varepsilon_{ijbt}, \qquad (1)$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i in time t defaults and zero otherwise. $Dummy(month \geq k)_{ijbt}$ is a dummy that takes the value of one for loans originated in or after month k and zero 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, whereas β_t denotes fixed effects for each calendar month. These fixed effects enable us to control for secular trends, including seasonal factors. β_b denotes fixed effects at the borrower level, which helps us to control for time-invariant borrower characteristics. Therefore, we effectively compare loans originated before and after month k at a borrower level. 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 ($k = 21, 22, \ldots, 35$) remains insignificant until 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 compared with loans issued until the 26^{th} month of an officer's tenure in a branch. For all of the months thereafter (that is, 28–35), the coefficient is not only positive and significant but also, monotonically increasing in magnitude.

5.2.2. Examining Loans that Actually Straddle. We first conduct an officer-level univariate test. The results are presented in Table A.1 of the online appendix. We find that, of the 44 loan officers, 36 officers see an increase in default rates for loans that straddle compared with those that do not. We conduct multivariate tests of our main hypothesis by identifying loans that actually straddle between two officers.

Figure 2. (Color online) Loan Default Rates Based on Loan Officer Tenure



We compare the default rates of such loans with other loans. We estimate the following regression:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_k \times Straddle_{-ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt}. \quad (2)$$

The dependent variable *Straddle* is a dummy variable that takes the value of one for loans that meet the definition of straddled loans as described; otherwise, it takes the value of zero. All other terms have the same meaning as in Equation (1). We also include a vector of controls denoted as X_{ijt}. We include loan size to control for the possible correlation between the size of the loan and its performance. These differences could arise for reasons such as technology used by the farmer, incentives to strategically default (Breza 2012), and evergreening of loans (Banerjee and Duflo 2014, Tantri 2018b), which could potentially vary based on loan size and officer tenure. As we discussed in Section 3.3, agricultural lending in India is based primarily on nonverifiable information. Therefore, the loan officer has to learn about the process of acquiring nonverifiable information relating to the borrower. Consequently, we include the loan officer's tenure as a control variable. We control for repeat borrowing to account for the impact of relationship banking.

The results are reported in Table 3. As shown in the table, the default rate of straddled loans is higher by 43.2%–48.1% depending on the specification used. The result shows that deterioration in loan performance is, indeed, caused by loans that are *actually* handled by two loan officers.

5.2.3. Tests Exploiting Discontinuity Provided by the Actual Date of Transfer. Our conversation with the bank that provides the data showed that, depending on the circumstances of the rotation, the bank gives a notice period of 15 days to a month 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 shirking of responsibilities, which is induced by loan officer rotation. We use several windows starting from 7 days before and after rotation to 30 days before and after rotation. It is reasonable to assume that even the officers who move on unscheduled rotation are likely to know about their impending rotation during the time interval that we consider for this test and hence, can plan their moves accordingly. Therefore, we include all 44 officers in the sample. We estimate the following regression equation:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_k \times Before\_Rotation\_k_{ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt}, \quad (3)$$

where $Default_{ijbt}, \beta_i, \beta_t$ and X_{ijt} are defined as before. *Before_Rotation_k* is a dummy variable that takes the value of one for loans originated within k days before actual rotation and zero otherwise. k refers to the before and after interval used. The sample is restricted to loans issued within an interval of k days before and k days after the actual rotation date. We include officer fixed effects and year fixed effects.[9]

The results are reported in Table 4. In column (1) of Table 4, we use an interval of seven days before and

Table 3. Effect of Mandatory Loan Officer Rotation on Loan Default Using Loans Straddling Across Two Officers

	(1)	(2)	(3)	(4)
Dependent variable		*Default*		
Straddle	0.432***	0.474***	0.424***	0.481***
	[54.083]	[55.529]	[42.475]	[33.378]
Repeated	−0.044***	−0.067***	−0.076***	
	[−6.038]	[−9.318]	[−10.687]	
Loan Size	0.015***	0.017***	0.017***	0.108***
	[5.974]	[6.545]	[6.895]	[15.509]
Current Tenure	−0.017***	−0.019***	0.000	−0.019***
	[−37.283]	[−34.874]	[0.052]	[−23.584]
Officer fixed effect	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes
Borrower fixed effects	No	No	No	Yes
Officer × month fixed effects	No	Yes	Yes	No
Year fixed effects	No	No	Yes	No
Observations	29,353	29,353	29,353	29,353
Number of borrowers	15,489	15,489	15,489	15,489
Adjusted R^2	0.239	0.308	0.318	0.154

Notes. We present ordinary least square (OLS) regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_k \times Straddled\_Loan_{ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt},$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i at time t defaults and zero otherwise. $Straddled\_Loan_{ijbt}$ is a dummy that takes the value of one for loans originated by one officer and serviced by another. *Repeated* equals one if the borrower b has previous loan(s) and 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 brackets below the regression estimates.

***Statistical significance at the 1% level.

after rotation. We increase the interval to 15, 21, and 30 in subsequent columns. As shown in the table, the default rate of loans issued just prior to the rotation is higher by between 34.9% and 43.4%. Given that the loans on both sides of the cutoff are issued 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.

5.2.4. Examining Loans that Are Expected to Straddle. In subsequent tests, we examine 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 could introduce forward-looking bias. As we have shown in Figure 1, for administrative reasons, the actual date of rotation may vary from the expected date (end of 36 months). 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. As argued before, we first restrict all of our tests to the group of officers who move on a scheduled rotation. Having shown the results for all months from 21 to 36 in Figure 2, we here test for the last six, three, and one month of an officer's expected tenure. Because the maximum tenure equals 39 months in our sample and the expected tenure equals 36 months, loans originated in the last 6 months or later are certainly affected by job rotation. We use the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_1 \times Last\_N\_Months_{ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt}. \quad (4)$$

All of the terms have the same meaning as in Equation (2). The results for these tests are presented in Table 5. Every officer is expected to rotate out of her current position in 36 months. *Last_N_Months* equals one if the loan was made any time after the loan officer had spent 36 − N months in the current assignment and zero otherwise. In columns (1) and (2) of Table 5, we consider the last six months. In columns (3) and (4) of Table 5, we consider the last three months. In columns (5) and (6) of Table 5, we consider the last one month. In columns (2), (4), and (6) of Table 5, we add fixed effects for each borrower. Across columns (1)–(6) of Table 5, we notice that the probabilities of default on loans originated in the last six, three, and one month of expected tenure are higher than those on

Table 4. Effect of Mandatory Loan Officer Rotation on Loan Default Using Discontinuity Provided by Actual Rotation

	(1)	(2)	(3)	(4)
Dependent variable		*Default*		
Interval, days	7	15	21	30
Before Rotation	0.393***	0.349*	0.434***	0.408**
	[2.790]	[1.679]	[2.927]	[2.217]
Loan Size	0.031	0.030*	0.027**	0.063***
	[1.420]	[1.897]	[2.198]	[3.171]
Current Tenure	0.081***	0.068***	0.068***	0.060***
	[5.007]	[4.057]	[4.696]	[3.810]
Officer fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,119	2,299	3,275	4,844
Number of officers	30	35	39	39
Adjusted R^2	0.302	0.362	0.359	0.357

Notes. We present OLS regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_k \times Before\_Rotation\_k_{ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt},$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i at time t defaults and zero otherwise. The explanatory variable of interest $Before\_Rotation\_k_{ijbt}$ takes the value of one for loans lent immediately before the rotation and zero otherwise. The sample is restricted to 7 days before and after rotation in column (1), 15 days before and after rotation in column (2), 21 days before and after rotation in column (3), and 30 days before and after rotation in column (4). Loans lent by all 44 officers are considered. The standard errors are clustered at an officer level, and adjusted t statistics are reported in brackets below the regression estimates.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

loans originated earlier by 10%, 18%, and 22%, respectively. This difference in the economic magnitudes supports the evidence in Figure 2 and suggests shirking of responsibilities by the loan officers.

5.3. 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. Thus, during the last few months of her tenure, if a loan officer issued loans to borrowers who have defaulted previously, then her replacement can certainly dig this information and present it to her 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 her tenure than at the beginning of her tenure.

To test this thesis, we first conduct a straightforward univariate test. We first limit the sample to repeat loans. Of 29,353 loans lent by officers moving on scheduled rotation, 14,239 are repeat loans. We define a variable *Lag_Default* that takes a value of one if the borrower b defaulted on the loan prior to the loan j under consideration and zero otherwise. We then compare the *Lag_Default* variable for loans that straddle and loans that do not. We find that the prior default rate of straddled loans is, in fact, 11.4% lower than the prior default rate of nonstraddled loans.

We then conduct a multivariate test. We modify the specification used in Equation (1) by using prior credit history as the explanatory variable. The explanatory variable is a dummy that takes the value of one if the previous loan issued to a borrower defaulted and zero otherwise. By construction, this test is run on the sample of repeat borrowers. We test whether previous loan history explains the probability of having a loan toward the end of an officer's tenure. Therefore, in different specifications, the variables *Straddle* and $Last\_N\_Months_{ijbt}$ are dependent variables. K takes the values of six, three, and one in different specifications.

The results are presented in Table 6. 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 toward the end of her tenure for fear of leaving verifiable evidence of a dubious loan. Similarly, we examine whether job rotation has any impact on the number and value of loans, both of which are verifiable. Expectedly, we do not find a significant impact. We report the results in Table A.2 of the online appendix and explain them in detail in Section V.B of the online appendix.

Note that, if the results obtained in Table 5 were owing to differences in verifiable information, then such as in Hertzberg et al. (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 on borrowers of an agricultural loan is whether they have defaulted on an earlier loan. Thus, the results in Table 6 further support the claim that the dark side of job rotation manifests itself only when the individual contribution of each agent cannot be verified. More so, as argued in Section 1, these results highlight that our results do not stem from the bank not caring about default on the loans originated by its loan officers.

5.4. 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 issued toward the end of her predecessor's tenure is likely to be low. Hence, such loans are likely to be of inferior quality. Naturally, she is likely to be wary of lending to those borrowers even if they repay their loans.

We, therefore, investigate whether the new loan officer discriminates between borrowers who were handled by the outgoing loan officer toward the end of her tenure vis-à-vis other borrowers. We implement the regression Equation (2) with dependent

Table 5. Effect of Mandatory Loan Officer Rotation on Loan Default

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			*Default*			
Last Six Months	0.100***	0.114***				
	[7.745]	[5.622]				
Last Three Months			0.175***	0.143***		
			[8.469]	[4.270]		
Last One Month					0.216***	0.319***
					[4.255]	[4.373]
Repeated	−0.069***		−0.063***		−0.063***	
	[−8.892]		[−8.175]		[−8.179]	
Loan Size	0.017***	0.121***	0.020***	0.120***	0.020***	0.121***
	[6.066]	[15.774]	[5.914]	[15.564]	[6.093]	[15.638]
Current Tenure	−0.006***	−0.005***	−0.003***	−0.003***	−0.002***	−0.003***
	[−12.331]	[−6.021]	[−11.737]	[−4.649]	[−10.412]	[−4.383]
Officer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	No	Yes	No	Yes
Officer × calendar 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^2	0.229	0.548	0.229	0.547	0.228	0.547

Notes. We present OLS regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_1 \times Last\_N\_Months_{ijbt} + \beta \cdot X_{ijt} + \varepsilon_{ijbt},$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i at time t defaults and zero otherwise. Every officer is expected to rotate out of her current position in 36 months. $Last\_N\_Months_{ijbt}$ equal one if the loan was made any time after the loan officer had completed $36 - N$ months in the current assignment and zero otherwise. *Last Six Months* equals one if the loan was made any time after the loan officer had completed 30 months in the current assignment and zero otherwise. *Last Three Months* equals one if the loan was made any time after the loan officer had completed 33 months in the current assignment and zero otherwise. *Last One Month* equals one if the loan was made any time after the loan officer had completed 35 months in the current assignment and 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 brackets below the regression estimates.

***Statistical significance at the 1% level.

variables indicating possible credit rationing. We report the results in Table 7. In columns (1) and (2) of Table 7, the dependent variable is a dummy variable that takes the value of one if a borrower receives a new loan within 180 days of repaying an existing loan and zero otherwise. In columns (3) and (4) of Table 7, 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 two parameters. We consider loans that actually straddle from one officer to the other 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) and (2) of Table 7, those borrowers who took a loan during the tenure of the previous loan officer and subsequently, saw a change in loan officers before they repaid the loan have an approximately 11.6%–16.6% lower likelihood of getting a loan within six months of their repayment. In columns (3) and (4) of Table 7, we find that the new loan officer takes approximately 38–39 more days to grant a new loan to those borrowers whose previous loan was issued by the outgoing loan officer. In sum, the results presented in Table 7 suggest that the incoming loan officers significantly curtail credit to borrowers who borrowed loans toward the end of the previous officer's tenure both by outright rejection and by significantly delaying the granting of new loans.

6. Alternative Explanations

6.1. Discontinuation of Evergreening

It is known that loan officers are more likely to evergreen loans lent to borrowers with whom they have an existing and long-term relationship (Banerjee and Duflo 2014, Tantri 2018b, Acharya et al. 2019). A loan officer has little incentive to evergreen a loan by issuing a new loan in cases where the initial loan was not lent by her. A default in such cases is less likely to

Table 6. Mandatory Loan Officer Rotation and Borrower Credit History

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	*Straddle*		*Last Six Months*		*Last Three Months*		*Last One Month*	
Lag Default	−0.012***	−0.007**	−0.031***	−0.052***	−0.045***	−0.024***	−0.010***	−0.007
	[−5.103]	[−2.028]	[−4.756]	[−4.518]	[−9.398]	[−2.741]	[−2.850]	[−1.307]
Repeated	−0.011***		−0.025***		−0.077***		−0.024***	
	[−6.057]		[−3.105]		[−12.142]		[−6.474]	
Loan Size	0.004***	−0.001	0.014***	0.009	−0.002	−0.011	0.006***	−0.005
	[5.419]	[−0.410]	[5.269]	[0.930]	[−0.961]	[−1.363]	[4.613]	[−1.015]
Current Tenure	0.002***	0.002***	0.029***	0.027***	0.017***	0.014***	0.005***	0.004***
	[9.893]	[6.273]	[59.497]	[39.271]	[39.455]	[24.798]	[16.565]	[11.078]
Officer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Officer × calendar month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,239	14,239	14,239	14,239	14,239	14,239	14,239	14,239
Number of borrowers	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Adjusted R^2	0.311	0.00948	0.652	0.51	0.776	0.603	0.661	0.409

Notes. We present OLS regression results using the following specification:

$$Last\_N\_Months\_ijbt = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_1 \times Lag\_Default_{ijbt} + \beta X_{ijt} + \varepsilon_{ijbt},$$

where $Last\_N\_Months_{ijbt}$ equals one if a loan j is issued to borrower b by officer i in the last N months. $Lag\_Default_{it}$ equals one if the borrower i has defaulted in his previous loan. In columns (1) and (2), it takes the value of one for loans that are handled by more than one officer and zero otherwise. Every officer is expected to rotate out of her current position in 36 months. *Last Six Months* equals one if the loan was made any time after the loan officer had completed 30 months in the current assignment and zero otherwise. *Last Three Months* equals one if the loan was made any time after the loan officer had completed 33 months in the current assignment and zero otherwise. Finally, *Last One Month* equals one if the loan was made any time after the loan officer had completed 35 months in the current assignment and 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 brackets below the regression estimates.

**Statistical significance at the 5% level; ***statistical significance at the 1% level.

be entirely attributed to the current loan officer because the loan was screened by someone else. Therefore, it is important to consider the possibility that our results are because of the outgoing officer evergreening loans by lending new loans toward the end of her tenure and the new officer refusing to further evergreen those loans, leading to higher default of straddled loans. In this case, our favored "shirking" explanation gets challenged. Even then, as long as the new loan officer or the bank management is not able to verify the efforts or the information set of the outgoing officer, our soft information story is valid, and our results will continue to differ from those of Hertzberg et al. (2010), where rotation acts as a deterrent against dubious lending. However, more explanation and testing are required to distinguish the unearthing of evergreening from shirking.

We conduct three tests for this purpose. First, we examine loans that were expected to be affected by job rotation but did not get affected. This situation occurs primarily because of the delay in loan officer rotation caused by administrative exigencies. Given the expected tenure of 36 months, all such loans are issued after 24 months of service. 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 were expected to but were not affected by rotation and loans that were neither expected to be nor were actually affected by rotation. These two groups constitute the treatment and control groups, respectively. An example is likely to make the point clear. Consider a loan officer who stayed in office for 39 months because of administrative reasons. Now consider a loan borrowed toward the end of the 26th month. Normally, this loan is expected to move, and hence, as per our "shirking" hypothesis, the incumbent is expected to reduce effort with respect to this loan. Compare this with another loan lent in say the 12th month. This loan is neither expected to move nor actually moves out of the outgoing officer's tenure, and hence, the officer is unlikely to shirk. Most notably, the new officer has no role to play in both the treated and control loans. Therefore, whatever may be the result, they are not likely to be caused by the new officer refusing to roll over loans evergreened by the outgoing officer.

We report the results in Table 8. We use officer and month fixed effects in column (1) Table 8 and officer × month fixed effects in column (2) of Table 8. We also use loan-level control variables. We find that the

Table 7. Mandatory Loan Officer Rotation and Credit Rationing

	(1)	(2)	(3)	(4)
Dependent variable	*Rationed*	*Rationed*	*Nextgap*	*Nextgap*
Straddle	0.149***	0.040***	39.760***	32.864***
	[19.683]	[3.055]	[8.730]	[4.326]
Repeated	−0.047***	0.236***	9.012***	23.173***
	[−6.685]	[21.088]	[2.850]	[4.806]
Loan Size	−0.017***	0.018***	4.305**	0.173
	[−6.163]	[3.160]	[2.549]	[0.054]
Officer fixed effect	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	No	Yes
Officer × month fixed effects	Yes	No	Yes	No
Observations	29,350	29,350	18,937	18,937
Number of borrowers	15,489	15,489	9,890	9,890
Adjusted R^2	0.217	0.369	0.0737	0.497

Notes. We present OLS regression results using the following specification:

$$Y_{ijbt} = \beta_0 + \beta_i + \beta_b + \beta_t + \beta_1 \times Straddle_{ijbt} + \beta X_{ijt} + \varepsilon_{ijbt},$$

where in columns (1) and (2), Y_{ijbt} equals one if no loan is issued to a borrower within 182 days of repayment of loan j issued by officer i to a borrower b during time t. In columns (3) and (4), the dependent variable *Nextgap* 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 *Straddle* takes the value of one for loans that are handled by more than one officer and zero otherwise. Officers experiencing scheduled rotation (tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at the borrower level, and adjusted t statistics are reported in brackets below the regression estimates.

**Statistical significance at the 5% level; ***statistical significance at the 1% level.

default rate of treatment loans is higher by 15.2% compared with control loans. If the loans issued during the 26th month were a part of an evergreening exercise, then they should not have systematically defaulted more. This is because the same officer who issued the loan in the first place continued even during its due date (26 + 12 = 38 months of tenure). An officer is unlikely to expose her own evergreening. She might have rolled over the loan further. The result is in line with the shirking hypothesis, which says that the incumbent does not collect sufficient soft information on loans that are expected to move out of her tenure.

Second, we restrict the sample to borrowers to whom the outgoing loan officers lent only once. Here, the treated loans are those where the borrower borrowed only once from the outgoing officer just before rotation, and her loans moved to the new loan officer. The control loans are those where the borrower borrowed only once from the outgoing loan officer, but the loan did not move to the incoming officer. Because the outgoing loan officer is dealing with the borrowers for the first time, the questions of the evergreening of loans and the subsequent revelation by the incoming officer do not arise. Therefore, if the evergreening explanation is correct, then we should not find higher default among treated leans. We report the results in Table A.3 of the online appendix. Even in this subsample, we find that the loans that move owing to rotation default more.

Third, to address political economy issues, we separately identify election years. As noted by Cole (2009) and Tantri and Thota (2017), state elections in India are held once in five years, and different states have different cycles for exogenous reasons. We test whether our results are mainly caused by politically driven lending to either garner votes or thank the voters after elections. We identify state election years for three states in our sample and test whether our results are driven by either increased evergreening or politically driven lending during elections. Specifically, we define a dummy variable—*Election*—that takes the value of one if the state under consideration has a scheduled election within a specified period of time. For robustness, we consider four different intervals around elections: one year before elections, six months before election, one year before and after elections, and six months before and after elections. We then interact the election variable with our straddle dummy that represents loans that move. We find that our main result goes through even after accounting for elections. The results are reported in Table A.4 of the online appendix.

6.2. Complementarity Between Monitoring and Screening?

Suppose that the screening and monitoring tasks are complementary to each other. For instance, a loan officer collects soft information about a potential

Table 8. Job Rotation and Destruction of Complementarity

	(1)	(2)
Dependent variable	*Default*	
Treatment Loans	0.325***	0.152***
	[17.754]	[5.854]
Repeated	−0.021**	−0.039***
	[−2.131]	[−4.209]
Loan Size	0.040***	0.037***
	[12.704]	[11.042]
Current Tenure	−0.019***	−0.019***
	[−34.473]	[−28.089]
Officer fixed effect	Yes	No
Calendar month fixed effect	Yes	No
Officer × month fixed effect	No	Yes
Observations	17,616	17,616
Number of borrowers	10,167	10,167
Adjusted R^2	0.255	0.325

Notes. We present OLS regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_1 \times Treatment\_Loans_{ijbt} + \beta X_{ijt} + \varepsilon_{ijbt},$$

where $Default_{ijbt}$ equals one if a loan defaults and zero otherwise. The explanatory variable of interest *Treatment_Loans* is a dummy variable that takes the value of one for loans issued after the 24^{th} month of an officer's tenure and falling due during the tenure of the same loan officer; otherwise, it is zero. The loans that actually straddle are excluded from the sample. Officers experiencing scheduled rotation (that is, tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at the borrower level, and adjusted t statistics are reported in brackets below the regression estimates.

**Statistical significance at the 5% level; ***statistical significance at the 1% level.

borrower using her social network, such as in Fisman et al. (2017). Such information may also be critical for monitoring the loan. Such social networks and 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 because she lacks the necessary soft information. Therefore, job rotation may destroy the complementarity between screening and monitoring and thereby, adversely affect loan performance.

We draw the reader's attention to the results presented in Table 8. Here, we find that loans that were expected to straddle but did not straddle default more than loans that were neither expected to straddle and also, did not straddle. Note that, in both sets of loans, there is no destruction of complementarity between screening and monitoring because the same loan officer handles the entire lifecycle of a loan. Because the sample for these tests was created using loans not affected by the destruction in complementarity and yet, loans that were expected to straddle default more, we can infer that our results do not stem from the same.[10]

6.3. Disruption of Borrower-Loan Officer Relationship?

As described in Section 3.2, agricultural lending in our setting is based primarily on nonverifiable information. Therefore, the relationship between the loan officer and the borrower can affect loan performance significantly (Drexler and Schoar 2014). Job rotation destroys the relationship between the loan officer and the borrower. Thus, it is possible that our results stem from a breakdown of the loan officer's relationship with the borrower and are not because of shirking.

Note that the results presented in Table 8 are inconsistent with the hypothesis. There is no breakdown in the relationship between the loan officer and the borrower, and yet, the group of loans that were expected to rotate but did not rotate underperforms those that were neither expected to rotate nor actually rotated.

Nonetheless, to investigate this concern further, we examine the effect of job rotation on loan performance of borrowers having a past relationship with the loan officer and others. We use the following specification:

$$\begin{aligned} Default_{ijbt} = {} & \beta_0 + \beta_i + \beta_t + \beta_b + \beta_1 \cdot Last\_N\_Months_{ijbt} \\ & + \beta_2 \cdot Sameofficer_j \\ & + \beta_3 \cdot Last\_N\_Months_{ijbt} \\ & \times Sameofficer_j + \beta_4 \cdot X_{ijt} + \varepsilon_{ijbt}, \end{aligned} \quad (5)$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i in time t defaults and zero otherwise. $Last\_N\_Months_{it}$ is defined the same way as in Equation (4). *Sameofficer* is a dummy variable that takes the value of one 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 zero. Thus, *Sameofficer* captures the difference between loans issued to borrowers having a past relationship with the loan officer and others. The coefficient β_3 represents the difference-in-differences estimate.

If the results in Table 5 stem only from the disruption in the relationship caused by rotation, then the deterioration in loan performance should be restricted to loans where there is a breakdown in relationship banking. There should be no effect on loans not affected by the disruption in the relationship. In Table 9, we report the results from the tests. The coefficient estimate for β_1 is significant in all cases. In other words, deterioration in loan performance is not restricted only to borrowers having an existing banking relationship with the outgoing officer. The coefficient estimate for β_3 is not always significant and flips sign based on the length of the end of the tenure period used.

Table 9. Relationship Banking vs. Mandatory Loan Officer Rotation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable				*Default*				
Straddle	0.427***	0.661***						
	[14.893]	[8.714]						
Last Six			0.066**	0.051				
			[2.121]	[0.766]				
Last Three					0.224***	0.642***		
					[2.689]	[2.951]		
Last One							0.401**	0.687*
							[2.407]	[1.711]
Same officer	0.074**	0.216***	0.076**	0.165***	0.088***	0.168***	0.092***	0.161***
	[2.464]	[4.253]	[2.392]	[3.058]	[2.775]	[3.112]	[2.863]	[3.008]
Same officer × *Straddle*	0.055*	−0.166**						
	[1.928]	[−2.166]						
Same officer × *Last Six*			0.068**	0.021				
			[2.487]	[0.329]				
Same officer × *Last Three*					0.036	−0.479**		
					[0.420]	[−2.132]		
Same officer × *Last One*							−0.012	−0.195
							[−0.071]	[−0.473]
Repeated	−0.100***	0.153***	−0.099***	0.177***	−0.104***	0.174***	−0.110***	0.180***
	[−3.356]	[3.073]	[−3.111]	[3.370]	[−3.267]	[3.314]	[−3.425]	[3.417]
Loan Size	0.001	0.067***	0.008*	0.074***	0.006	0.075***	0.006	0.074***
	[0.360]	[5.563]	[1.941]	[5.406]	[1.442]	[5.392]	[1.475]	[5.353]
Current Tenure	−0.023***	−0.036***	−0.011***	−0.023***	−0.011***	−0.023***	−0.011***	−0.023***
	[−31.150]	[−25.534]	[−15.139]	[−15.569]	[−16.362]	[−17.071]	[−15.735]	[−17.055]
Officer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Officer × month fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Observations	14,239	14,239	14,239	14,239	14,239	14,239	14,239	14,239
Number of borrowers	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Adjusted R^2	0.331	0.276	0.265	0.169	0.267	0.171	0.266	0.176

Notes. We present OLS regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_i + \beta_t + \beta_b + \beta_1 \cdot Last\_N\_Months_{ijbt} + \beta_2 \cdot Sameofficer_j + \beta_3 \cdot Last\_N\_Months_{ijbt} \times Sameofficer_j + \beta_4 \cdot X_{ijt} + \varepsilon_{ijbt},$$

where $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i at time t defaults and zero otherwise. Every officer is expected to rotate out of her current position in 36 months. *Last Six* equals one if the loan was made any time after the loan officer had spent 30 months in the current assignment and zero otherwise. *Last Three* equals one if the loan was made any time after the loan officer had spent 33 months in the current assignment and zero otherwise. Finally, *Last One* equals one if the loan was made any time after the loan officer had spent 35 months in the current assignment and zero otherwise. In columns (7) and (8), it takes the value of one for loans that are handled by more than one officer and zero otherwise. *Straddle* takes the value of one for loans that are handled by more than one officer. Otherwise, it takes the value of zero. *Sameofficer* is a dummy variable that takes the value of one if the same loan officer issues the loan under consideration as well as the previous loan to the same borrower; otherwise, it takes the value of zero. Officers experiencing scheduled rotation (tenure not less than 33 months) form the sample for these tests. The standard errors are clustered at the borrower level, and adjusted t statistics are reported in brackets below the regression estimates.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

6.4. Disruption of Learning Owing to Job Rotation?

Could it be the case that the results stem from a disruption in learning caused by job rotation? The loans issued toward 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 issued immediately prior to and after the rotation. If the officer takes time to learn, then the new loans issued by her during the beginning of her tenure are expected to default even more. However, the results presented in Table 4 show that this is not the case.

Second, we ask whether, within straddled loans, loans that straddle from officers moving from scheduled rotation default more. Note that the new loan officer learning is common in both the cases. In other words, disruption in learning occurs with scheduled rotations as well as unscheduled rotations. Thus, if a disruption in learning by the incoming officer drives our results, then the observed deterioration in loan performance should also manifest itself for the group of loan officers transferred on unscheduled rotation. Any incremental effect is more likely to be because of shirking than loan officer learning.

We estimate the following regression:

$$Y_{ijbt} = \beta_0 + \beta_b + \beta_t + \beta_1 \cdot Scheduled\_Rotation_{ijbt} + \beta_2 \cdot X_{ijt} + \varepsilon_{ijbt}. \quad (6)$$

The data are organized at the loan level and restricted to loans that straddle. We include all officers in the sample. *Scheduled_Rotation* is a dummy variable that takes the value of one if the officer under consideration moves because of scheduled rotation and zero otherwise. All of the terms have the same meaning as in Equation (2).

In columns (1) and (2) of Table 10, we notice that the coefficient of scheduled rotation dummy is positive and significant. This evidence suggests that, although officers take the time to learn, the results presented in Table 5 cannot be explained by the disruption in learning, such as in Di Maggio and Van Alstyne (2012).[11]

6.5. Loan Officer Caution Close to Job Rotation

There is a possibility that our main result is owing to caution by loan officers close to job rotation. It is possible that loan officers make small loans to new borrowers to know their character and that such behavior manifests more just before job rotation. The intention is to increase the loan size after the loans become seasoned. This situation can lead to higher default rates when we consider only the number of loans and do not consider their value. However, this is a result of caution and not the result of shirking of

Table 10. Loan Default on Various Subsamples for Straddled Loans and for Loans Disbursed by Officers Who Face Unscheduled Rotation

	(1)	(2)	(3)	(4)
Dependent variable	*Default for Straddled Loans*		*Default on Unscheduled Rotation*	
Scheduled	0.172***	0.538***		
	[8.671]	[5.784]		
Straddle			0.407***	0.329***
			[57.896]	[14.340]
Repeated	−0.187***	0.111***	−0.129***	0.258***
	[−24.361]	[2.842]	[−15.051]	[10.394]
Loan Size	−0.021***	0.002	−0.004	0.143***
	[−7.088]	[0.101]	[−1.085]	[8.585]
Current Tenure	−0.006***	−0.020***	−0.040***	−0.054***
	[−7.766]	[−4.470]	[−75.857]	[−30.282]
Calendar month fixed effects	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	No	Yes
Observations	17,264	17,264	14,419	14,419
Number of borrowers	13,904	13,904	9,485	9,485
Adjusted R^2	0.0718	0.0650	0.523	0.562

Notes. We present OLS regression results using the following specification:

$$Default_{ijbt} = \beta_0 + \beta_t + \beta_b + \beta_1 \cdot Scheduled_{ijbt} + \beta_2 \cdot X_{ijt} + \varepsilon_{ijbt}$$

in the subsample of only straddled loans and

$$Default_{ijbt} = \beta_0 + \beta_t + \beta_b + \beta_1 \cdot Straddle_{ijbt} + \beta_2 \cdot X_{ijt} + \varepsilon_{ijbt}$$

in the subsample of loans disbursed by officers who face unscheduled rotation. $Default_{ijbt}$ equals one if loan j issued to borrower b by officer i at time t defaults and zero otherwise. We restrict the sample only to straddled loans in columns (1) and (2) and to loans lent by officer rotated out by unscheduled rotation for columns (3) and (4). $Scheduled_{ijbt}$ is a dummy that takes the value one if loan officer i is rotated after completion of 33 months (scheduled rotation). $Straddle_{ijbt}$ is a dummy that takes the value of one for loans j originated by one officer and serviced by another and zero otherwise. The standard errors are clustered at borrower level, and adjusted t statistics are reported in brackets below the regression estimates.

***Statistical significance at the 1% level.

responsibilities. We examine the amount in default (in Table A.5 of the online appendix), the probability of a new borrower obtaining a loan (Table A.6 of the online appendix), and the amount of the loan lent to new borrowers (Table A.7 of the online appendix). The results are inconsistent with the loan officer caution hypothesis. We explain the results in detail in Section V.C of the online appendix.

7. Who Shirks?

The results presented so far support the hypothesis that the outgoing loan officer shirks while screening loans that she expects to move to a new officer postrotation. Notice that even those loans that were initially expected to move but did not move because of an exogenous delay in rotation default more. The evidence supports the view that outgoing officers engage in planned reduction of effort. In this context, it is pertinent to ask whether the incoming officer also shirks in monitoring. In Section 3.5, we discuss in detail the monitoring role of the incoming officer. Given that management cannot ascribe clear responsibility on straddled loans because of soft information, it is possible that even the incoming officer shirks in monitoring the straddled loans.

Admittedly, we do not have strong evidence to show shirking by the incoming officer. We point out two results that indicate that even the incoming officer shirks. First, as shown in Figure 2, we find a monotonic increase with time in the probability of default for loans originated after the 27$^{\text{th}}$ month. Note that almost all loans originated after the 27$^{\text{th}}$ month are almost certain to be affected by job rotation. Thus, 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 could have possibly stemmed from differences in the degree of free riding on effort in monitoring the loans (by the incoming loan officer). Consider a loan lent in the 33rd month and a second loan lent in the 36$^{\text{th}}$ month. Given that both the loans have almost similar probability of moving out of the outgoing officer's tenure, it is unlikely that her screening effort will be different. However, the length of time that the incoming officer spends in monitoring differs between the two loans. We find that the later loan has a higher chance of defaulting, suggestively indicating lax monitoring by the incoming officers.

Furthermore, within unscheduled rotations, we test whether straddled loans are more likely to default. We estimate Equation (2) and present the results in columns (3) and (4) of Table 10. If it is true that the incoming officer shirks in monitoring, she should shirk irrespective of the tenure of the officer who originated the loan. Given the use of soft information, it is difficult for the management to fully hold one of the officers responsible for such loans. If, however, there is no reduction in monitoring effort or if the monitoring is ineffective, then there should be no difference in loan performance of straddled and nonstraddled loans within the group of loans lent by officers moving on unscheduled rotation because there is less time available for outgoing officers to execute planned reduction of effort. Our results show that, even within the group of loans lent by officers moving on unscheduled rotation, straddled loans default more.

Despite the finding suggestively indicating lax monitoring, we consider the evidence at most suggestive because we do not have an exhaustive list of administrative exigencies under which a loan officer is moved out of a branch early and also, the criteria for selection of officers for early rotation. Finally, we do not have any information about the period of advance notice given in such cases.

7.1. Robustness Tests

We perform several other robustness tests. First, in tests that consider multiple loans borrowed by a single farmer, we cluster the errors at the borrower level because the most important determinant of crop performance is land and the resources available, such as irrigation and quality of fertilizers among others. The innate ability of farmers, which includes their technical knowhow regarding agriculture, also determines crop performance and hence, loan performance. However, we recognize that there could be variations at the officer level. Therefore, as a robustness exercise, we reestimate all of the tests by clustering at the officer level. Our results hold. We present the results in Tables A.8–A.15 of the online appendix. We consider all 44 officers in these tests.[12]

Second, there could be a concern that our results are driven by seasonality or limited to some branches. It is crucial to note that we use calendar month fixed effects and hence, account for seasonality. Nonetheless, as a further robustness test, we classify rotations into two categories: those done in busy seasons and those done in lean seasons. To coincide with school reopening timing and hence, avoid inconvenience to the loan officers, most of the rotations (61% in our sample as shown in Table A.16 of the online appendix) happen in June and July. Although the reason is exogenous, we repeat our main tests separately for rotations done in June and July (busy season) and those done in other months (lean season). Our results are replicated in both the subsamples. We present the results in Table A.17 of the online appendix. We also conduct our main test separately for each branch. We find that our results are replicated in 13 of 14 branches. We present the results in Table A.18 of the online appendix. Third, in Table A.19 of the online appendix, we also reestimate our results without using loan size and current tenure of the officer as explanatory variables. Our results hold, indicating that the results are not because of the addition of the controls.

Finally, as a further robustness test, we estimate Equation (2) (i) by using the number of days that a loan is outstanding in place of the dummy variable representing a default as the dependent variable (Table A.20 of the online appendix), and (ii) by estimating the linear probability model without officer- and borrower-level fixed effects (Table A.21 of the online appendix). The results hold. The results also hold if a probit model is used instead of an OLS model.

8. Discussion

It is important to discuss the role of the typical Indian institutional features. The crucial question is whether the results continue to hold in the absence of the specific institutional features. It is clear from the description of institutional features described in Section 3 that they are useful insofar as they amplify the use of soft information and make rotation exogenous. For instance, consider the fact that borrowers do not have credible records, such as tax returns or crop insurance details. These features ensure that the loan officer must rely heavily on soft information and significantly, reduce the role of hard information. One cannot infer that, if the borrowers had tax returns, soft information is not required. As mentioned in Section 3.3, crucial details, such as a borrower's honesty and integrity, susceptibility to shock, whether a borrower is undergoing liquidity or a fundamental shock, the quality of the standing crop, and a borrower's current inclination to default strategically among others, cannot be determined using only past records. There are instances where borrowers strategically default, even in more general settings (Guiso et al. 2013). Therefore, soft information will have a role to play in loan decisions, especially when the borrowers are individuals. Individuals do not usually maintain audited records of their transactions. In addition, it is difficult to verify transactions made by individuals using third-party records.

As we have seen in tests relating to the credit history of the borrowers, loan officers who shirk their responsibilities can ensure that loans that are impacted by rotation do not differ with respect to hard information. In case tax returns are available, the loan officers are likely to ensure that they do not shirk in assessing the information given in tax returns. Although the availability of hard information may reduce the magnitude of the impact (directionally), results will still hold as long as the dominance of soft information and job rotation are present. Similar arguments can be made concerning other features, such as bullet loan structure and government intervention. In case the loans are not bullet loans, loan officers can repeatedly evergreen loans until job rotation and ensure that all intermediate payments have been made on time until their rotation (Tantri 2018b).

In sum, although some institutional features are, admittedly, peculiar, our results do not exist only because of such features. These features act as catalysts in enhancing the use of soft information.

9. Conclusion

We show that job rotation leads to costs that have not yet been investigated in the literature. In particular, the *costs* that we highlight arise when decision making inside a firm is driven by soft information because the principal finds it difficult to fix responsibility when a task is undertaken by multiple agents. Innovative firms, which have dominated economic activity over the last two decades, rely primarily on nonverifiable actions (Aghion and Tirole 1994, Zingales 2000). Therefore, based on the evidence that we provide in this study, we conjecture that job rotation would be less common in innovative firms than in traditional firms that rely primarily on brick and mortar assets. Thus, a fruitful area for further investigation would be to examine how the net effect of job rotation varies with the structure of information used for decision making in a firm.

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Endnotes

[1] Some of the other papers that have studied job rotation include the following: Miller et al. (1973), Quartly (1973), Hirao (1993), Campion et al. (1994), Myers et al. (2003), Arya and Mittendorf (2004), Eriksson and Ortega (2006), Ho et al. (2009), Lennox et al. (2014), and Hakenes and Katolnik (2017).

[2] Note that, because of legal requirements on directed lending to agriculture in the Indian context, loans to defaulted borrowers are not uncommon (Bhue et al. 2016).

[3] Source: *The Hindu* (2020).

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

[5] Recently, the government of India launched a massive drive to open bank accounts (see Agarwal et al. 2017 and Chopra et al. 2017 for more details). However, the program was launched after our sample period.

[6] In Section I of the online appendix, we describe in detail the process of collection of soft information and also, the type of soft information collected.

[7] 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).

[8] Such operational deviations in the implementation of a three-year mandatory rotation rule are observed in Hertzberg et al. (2010) as well.

[9] We cannot use month fixed effects because we have minimal variation within some months given the short interval used. Similarly, we cannot use loan officer tenure as a control variable because the construction of the tests leaves minimal variation in this variable.

[10] It is worth noting that the treated loans for the test (issued during the last 12 months of expected service) are likely to be seasoned loans where a loan officer has collected significant soft information. This aspect may make such loans different from the control loans issued earlier in the loan officer's tenure. When examined carefully, one can see that the fact that the treated loans could contain seasoned loans only underestimates our results for this purpose because generally, seasoned loans are expected to default less.

[11] As we have pointed out in Table A.1 of the online appendix, the default rate on loans issued in the initial phase of an officer's tenure is higher than the default rate on loans issued at a later phase. In fact, this phenomenon continues until job rotation becomes imminent.

[12] In Table 4 only, we cluster the errors at an officer level because the sample used does not have multiple loans for a borrower.

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