Soft Information And The Cost Of Job Rotation: Evidence From Loan Officer Rotation*

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We highlight the *costs* from a principal rotating agents among tasks when decision-making inside a firm is driven by soft information. These costs arise because (i) an incoming agent cannot verify the information set that the outgoing agent utilised, and (ii) neither agent receives the entire marginal benefit/penalty for her effort. We provide evidence of this cost using unique loan and officer level data from a large public sector bank in India. Using the bank's fixed-tenure-based policy of loan officer rotation for *identification*, we find that default probabilities are 7.5% higher for loans affected by job rotation when compared to other loans. This difference is not explained by differences in hard information or the loss of a lending relationship.

Key Words: Agency Costs, Bank, Default, Hard Information, Loan, Rotation, Soft Information, Relationship Banking.
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I Introduction

This paper examines the policy of rotating agents between tasks in order to mitigate agency problems in communication within an organization. Few empirical studies have examined the implications of a well defined rotation policy. A notable exception is Hertzberg, Liberti, and Paravisini (2010), who study loan officer rotation in a bank and find that rotation policy creates incentives for the outgoing agent to reveal private information truthfully towards the end of her tenure, which leads to more efficient capital allocation. However, the possible costs associated with a rotation policy have not received attention in the empirical literature. In this paper, we argue that rotation policies can be costly when soft information dominates decision-making inside a firm. The cost we highlight stems from the inability to verify soft information. We provide evidence supporting our thesis using *unique* data for bank loans and the loan officers that make these loans. We find that mandatory rotation of loan officers leads to outgoing loan officers making lower effort when the officer's tenure in a bank branch is expected to come to an end. Such distortion in loan officer incentives, in turn, leads to inefficient capital allocation by the bank.

Delegation of tasks to agents is a reality in all organizations. While delegation induces the agent to maximize effort, it also leads to loss of control for the principal (Aghion and Tirole (1997); Stein (2003)). Delegating authority to an agent can also create other problems such as collusion, sub-optimal performance, etc. These problems stem from the fact that the agent, in her normal course of business, acquires private information that the principal has no access to. Moreover, the congruence between the interests of a principal and an agent vary with the nature of the task and the circumstances in which the task is carried out. Rotation of agents among tasks has been suggested as a solution for eliciting private information from agents (Arya and Mittendorf, 2004).

We argue that job rotation imposes costs when decision-making inside the firm is driven by soft information because (i) an incoming agent cannot verify the information set that the outgoing agent utilised, and (ii) neither agent receives the entire marginal benefit/penalty for her effort. We study this cost of job rotation inside a bank for the following reasons. First, because bank lending relies on relationships and soft information,[1] decision-making inside the bank provides an ideal setting to study this cost. Second, ex-post default on a loan represents a concrete and verifiable outcome measure that, in turn, depends upon unverifiable sets of information. Such an empirical setup is rarely available in other organizational settings.

In a bank, a rotation policy creates a peculiar situation with respect to loans lent during the end of a loan officer's tenure. By design, the outgoing and incoming officers

[1] See Ramakrishnan and Thakor (1984); Rajan (1992); Petersen and Rajan (1995); Petersen and Rajan (2002); Stein (2002); Petersen (2004); Berger, Miller, Petersen, Rajan, and Stein (2005).

become responsible for the performance of such a loan. While the outgoing loan officer is responsible for screening and due diligence at the time of lending, the incoming officer bears responsibility for monitoring and collecting the dues. Thus, job rotation transforms a simple incentive problem, where employee performance can be possibly rewarded based on how the loan performs, into a problem of moral hazard in teams (Holmstrom (1982)). If the efforts made by the incoming and outgoing officers are verifiable, then the firm can create incentive structures where each employee reaps the benefit/penalty proportional to his (measurable) contribution. Moreover, as Hertzberg, Liberti, and Paravisini (2010) highlight, if effort is verifiable then job rotation creates the possibility that the outgoing officer reveals his predecessor's effort. As a result, career concerns motivate the predecessor to provide effort optimally. However, when the information collected by the employee is soft, neither the information nor the effort at collecting the same can be verified. In this case, as in Holmstrom and Milgrom (1991), the number of observables—default on the loan in this case—is less than the number of activities performed by two different agents. Therefore, the firm cannot design an incentive contract that rewards each employee partially according to this effort. Using a simple theoretical model presented in Section IV, we show that a rotation policy therefore leads to an equilibrium where both the officers exert low effort for loans lent at the end of the outgoing loan officer's tenure.

This result is obtained due to the combination of two factors. First, due to the problem of moral hazard in teams, neither officer receives *in toto* the marginal benefit from (or penalty for) her effort. Second, when lending is based on soft information, the incoming loan officer finds it hard to verify the level of effort exerted by the outgoing officer in screening the loan. Similarly, the outgoing officer cannot verifiably prove to his superiors that the incoming loan officer may have exerted low effort in monitoring the loan and collecting the dues. Our second assumption is based on the fact that decision-making inside banks is dominated by soft information. This assumption is motivated not only by bank lending relying on soft information in general (Petersen (2004); Ramakrishnan and Thakor (1984)) but also by the findings in Fisman, Paravisini, and Vig (2012). They show in the Indian context that informal relationships between a loan officer and a borrower play a major role in lending and repayment decisions.

We test our hypothesis using *unique* data for bank loans and the loan officers that make these loans. This data was provided to us by a large public sector bank in India. Apart from internal audits, audit by the officials from the Reserve Bank of India ensures that our data are authentic. Even though the loan account data provided to us span the time period October 2005 to May 2012, we restrict our analysis to loans issued till May 2011. The agricultural crop loans that we employ for our analysis have a maturity of one year. Therefore, restricting our analysis to loans issued till May 2011 ensures that we have data on loan performance for all the loans in our sample. The data comprise of 45592 agricultural crop loans issued by 51 loan officers over the time period October

2005 to May 2011; of these 45592 loans, 25976 loans constitute repeat loans.

To identify the effect of job rotation on loan performance, as in Hertzberg, Liberti, and Paravisini (2010) and Fisman, Paravisini, and Vig (2012), we exploit the mandatory rotation policy employed at the bank. As part of this policy, the bank rotates its loan officers once the officer has completed three years in a particular branch. Typically, rotation of loan officers in a bank may be correlated with their prior performance, which would spoil identification. However, public sector banks in India are bureaucratic and operate based on rigid rules. As well, the employees of public sector banks in India are heavily unionised and oppose any rotation that deviates from the set rules.[2] Thus, in our setting, rotation of loan officers occurs based on a rule rather than as a reaction to loan officer performance. Though *de jure* loan officers should get rotated exactly after completing three years, *de facto* loan officer tenure exhibits some variation around three years. This variation comes about because a loan officer has to wait for a replacement to be identified and for the replacement to take over responsibilities from him, which leads to many loan officers' tenure being more than three years. On the other side of the spectrum, we inferred through our interviews with the bank officials and our review of official documents that administrative exigencies contribute to tenure of some loan officers being less than three years. Figure 2 shows how the likelihood of a loan officer remaining in her current job varies with her tenure. We observe a sharp discontinuity at three years, which illustrates that the bank's rotation policy of transferring officers after three years indeed operates on the ground.

We use the sample of agricultural crop loans made by the bank. Agricultural crop loans provide us two key advantages. First, as we argue in Section III.A, 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, we can cleanly separate loan officers into "treatment" and "control" groups to estimate the effect of a rotation policy. Because the expected tenure equals three years, an officer that has completed two-and-a-half years in office is more likely to make a loan that would straddle her tenure and that of her replacement. These officers represent our "treatment" group. In contrast, a loan officer that has not completed two-and-a-half years in office is less likely to be involved in such a loan. As in Hertzberg, Liberti, and Paravisini (2010), these officers represent our "control" group. Using these treatment and control groups, we estimate a difference-in-difference. For both the control and treatment groups, we estimate the difference in probability of default between loans issued in the last six months of an officer's tenure and loans issued earlier. The difference between these two differences provides an estimate of the effect of job rotation on loan performance. We estimate

[2]For example, the unions of State Bank of India—the largest public sector bank in India— opposed a recent transfer policy calling it a "harassment". Source: http://www.hindu.com/2010/11/16/stories/2010111652630300.htm

this effect after including fixed effects for each loan officer and each year in the sample, which enable us to control for unobserved loan officer characteristics and time trends respectively. We estimate that job rotation increases the probability of default by 10.7%. Apart from this difference-in-difference effect, we find the average performance of loans affected by job rotation to be lower: loans lent during the last six months of a loan officer's tenure default 2.6% more than loans lent earlier.

Could the above cost of job rotation stem from reasons unrelated to soft information? For example, could it be the case that a new loan officer faces a learning curve, which leads to the higher default rates on loans affected by job rotation as in Di Maggio and Van Alstyne (2012)? To disentangle the hypothesized effect from this alternative, we examine separately for the control and treatment groups the difference in the default rates on loans issued in the last six months of an officer's tenure vis-à-vis loans issued earlier. If learning necessitated by job rotation accounts for the above effects, then for both groups the default rates for loans issued in the last six months should be similarly high when compared to earlier loans. However, we find that for the control group of officers, default rates for loans issued in the last six months are *lower* than loans issued earlier. In contrast, for the treatment group of officers, default rates for loans issued in the last six months are higher than loans issued earlier. Thus, the above results are unlikely to result because the new loan officer faces a learning curve.

The above effects could also be due to lower effort in acquiring hard information rather than in collecting soft information. To distinguish these disparate effects, we examine the (bank's) credit history of borrowers who avail a crop loan in the last six months of a loan officer's tenure. In general, officers who spend longer time in a branch tend to chose borrowers with a better credit history. However, we find no difference between the treatment and control groups in the credit history of borrowers that received loans in the last six months of a loan officers' tenure vis-à-vis the credit history of borrowers that received loans in other periods. Because credit history represents hard information, this result demonstrates that the above differences in probability of default do not stem from differences in effort in obtaining hard information.

As well, the above results cannot be explained by the possibility that job rotation adversely affects loan performance by destroying the relationship between the borrower and the loan officer (see Drexler and Schoar (2011) for evidence of such effects). Since we include officer fixed effects in all our empirical specifications, our tests exploit variation within the loans originated by a loan officer. Moreover, we test and find that our results are not driven exclusively by repeat borrowers, where the effects due to the destruction of the relationship between the borrower and the loan officer would manifest.

Interestingly, we also find that the (incoming) new loan officer discriminates between borrowers who borrowed their previous loan during the tenure of the outgoing loan officer and those who borrowed their previous loan during her tenure: borrowers in the former

group have less chance of being given a new loan when compared to borrowers in the latter group. This evidence suggests that the incoming loan officer anticipates lack of (screening) effort on the part of the previous loan officer.

The rest of the paper proceeds as follows: Section II describes the literature and highlights our contribution. Section III provides the institutional background. Section IV describes a simple model that generates our thesis. Section V describes the data while Section VI explains our empirical results. Section VII concludes.

II Literature Review

Our study relates to the literature on banking as well as to the organizational economics literature that examines the role of information in organizational decision making. First, our study relates to a growing literature in banking that examines the incentive effects of loan officers on the quality of lending. We contribute to this literature by highlighting the perverse incentives created by job rotation when lending is based on soft information. In this respect, our study is closest to Hertzberg, Liberti, and Paravisini (2010), who show that impending loan rotation in a bank creates incentives for the incumbent agent to reveal information truthfully. The agent faces the threat of being exposed by the incoming agent, which would adversely impact her career prospects. While Hertzberg, Liberti, and Paravisini (2010) highlight this important benefit of job rotation, we focus on the costs stemming from job rotation in organizational environments where soft information dominates decision-making. Because bank lending inherently depends on soft information, we highlight this cost in the context of a bank.[3] In particular, we focus on agricultural loans provided to small farmers in India — a setting where loans are made primarily using soft information.

Liberti and Mian (2009) find that hierarchical and geographical distance between collectors of information and those who use the same in decision making reduce the importance of soft information in lending. Agarwal and Hauswald (2010) find that delegation of authority leads to increased production and utilization of soft information in decision making. Di Maggio and Van Alstyne (2012) argue that job rotation leads to destruction of human capital acquired over the years by loan officers, which leads to adverse loan performance. Agarwal and Ben-David (2014) find that change in incentives from fixed salary to volume-based pay increases aggressiveness of loan origination and leads to higher default. Cole, Kanz, and Klapper (2013) examine the effect of various performance-based compensation schemes for loan officers on the quality of lending done

[3]Among empirical studies that investigate job rotation, Arya and Mittendorf (2004) shows that job rotation can help a principal to know the true ability of the workers. Job rotation has also been considered a costless way of extracting information about the productivity of a job (Hirao (1993) and Arya and Mittendorf (2004)).

by loan officers. Berg, Puri, and Rocholl (2013) highlight the perverse incentives created by volume-based incentives when lending is based on hard information. Specifically, they find that the quality of lending is adversely affected in such settings because loan officers increasingly use multiple trials to move loans over the cut-off. Puri, Rocholl, and Steffen (2010) find that information about borrowers obtained from simple savings or checking accounts can help to improve loan performance.

Relatedly, our study also contributes to the banking literature that studies the use of soft versus hard information in bank lending. This literature identifies hard information with "transactions-based lending." Berger and Udell (2002), Stein (2002), Petersen and Rajan (2002), and Berger, Miller, Petersen, Rajan, and Stein (2005), among others, provide support for this link. Petersen and Rajan (2002), Berger, Miller, Petersen, Rajan, and Stein (2005), DeYoung, Glennon, and Nigro (2008) and Liberti and Mian (2009), Agarwal and Hauswald (2010) and Skrastins and Vig (2013) substantiate a positive link between geographical and hierarchical distance between the bank and the borrower and the use of hard information.

This study also relates to the literature examining agency problems that arise when agents have to communicate with each other inside a firm to facilitate decision-making. We contribute to the organizational economics literature by highlighting the costs of job rotation when decision making is based on soft information. Aghion and Tirole (1997) develop a theory of allocation of formal and real authority in an organization. Starting from the premise that a principal's preferred project need not be the best choice for the agent, they show that by delegating authority to an agent the principal loses some control over the project. However, such delegation increases the agent's initiative. They also show that the principal delegates more authority to the agent if the degree of congruence between the principal's and agent's project choices is high. Our study shows that the congruence between an agent's preferred actions and those of the principal is low when the agent finds it imminent that he/she would be rotated out of the job. Thus the agent (loan officer), whose actions align with the principal's interests in normal times, deviates from the principal's preferred action when job rotation is imminent. This divergence causes reduction in effort by the agent. The divergence happens in organizational environments where decision-making relies primarily on soft information because soft information is not verifiable and the agent realizes that he/she is not going to derive *in toto* the marginal benefit/penalty from her effort.

III Background

As institutional background, we describe agricultural lending in India and the nature of incentives faced by employees of public sector banks in India.

III.A Agricultural Lending in India

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

III.A.1 Importance of soft information

Agricultural lending in a developing country like India is based primarily on soft information. First, apart from routine information such as name, address, etc., the loan officer does not have access to any other relevant hard information. Because agricultural income in India is exempt from income tax,[4] small farmers, who do not have any other source of income other than agricultural income, do not file income tax returns. Neither is there any independent audit of the farmers' income. Given that nearly 44.1% of small farmers in India are illiterate (Mahadevan and Suardi, 2013), proper annual records of production are not maintained by small farmers. As well, no publicly available credit history exists for borrowers of agricultural loans in India.[5] The farmers in our sample are quite small: they have landholding of less than 2 hectares. In fact, nearly 82% farmers in India have landholding less than 2 hectares (Mahadevan and Suardi, 2013). Small farmers do not use modern technology as these involve fixed costs both in terms of learning and financial resources. Given the size of their landholdings, such fixed costs are disproportionately high. Nearly 65% of the small farmers depend on rain fed irrigation (Mahadevan and Suardi, 2013). As well, more than 75% of Indian farmers are not even covered by crop insurance (Mahul and Verma, 2012). Thus, a loan officer cannot use potentially hard information such as the use of irrigation and/or crop insurance. This deprives the loan officer of any "verifiable" source of information to assess the creditworthiness of an agricultural borrower.

Second, the literature on soft versus hard information argues that distance—both and hierarchical—determines crucially the use of hard versus soft information (see Petersen and Rajan (2002), Berger, Miller, Petersen, Rajan, and Stein (2005), Liberti and Mian (2009), Agarwal and Hauswald (2010) among others). We have observed during the data collection exercise that the branch manager, who is the loan officer in our sample, meets all the borrowers personally before sanctioning crop loans. The branch manager is located geographically proximate to the borrower and interacts regularly with them. Also, as part of the policy set by the bank, loans below the size of INR 0.65 million can

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

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

be sanctioned by the branch manager. Because the size of the agricultural crop loans in our sample are much smaller, the loan officer has the authority to sanction the small sized agricultural crop loans without having to seek the permission of an officer higher in the organizational hierarchy.

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 2012). The loan officers interactions with his borrowers are through the loan account and transactions related to the same. As a result, unlike in Puri, Rocholl, and Steffen (2010), loan officers cannot utilize information from savings or checking accounts to obtain hard information about the borrower.

III.A.2 Scarce collateral

A common solution to mitigate strategic default is to have the borrower post a physical asset, which can be appropriated upon default. However, most farmers in emerging economies are too poor to post any substantial collateral other than the land and the crop. Also, poorly delineated property rights over land exacerbate the problem by making it difficult for the bank to foreclose the land that has been put up as collateral for the loan. Moreover, foreclosing a farmer's land is extremely politically sensitive as local politicians, cutting across party lines, intervene on behalf of farmers.[6] In extreme cases, laws have been passed to render recovery of agricultural loans difficult; an example of this is the Andhra Pradesh Microfinance Institutions (Regulation and Moneylending) Act, 2010. Effectively, farmers in India do not face the threat of their land being taken over by their lenders, which encourages strategic default.

III.A.3 State controlled banking system

Government of India plays a dominant role in the banking sector. Government owned banks account for 74.2% (75.1%) of aggregate amount loans outstanding (deposits) in the banking sector. The Government of India nationalized many private banks in 1969 and 1980 and enforced several measures with the declared objective of improving access to finance to some "critical" sectors and to vulnerable sections of the population. Priority sector guidelines and branch expansion norms were the most impactful regulations issued (see Burgess and Pande (2003), Burgess, Pande, and Wong (2005), Cole (2009)). Priority sector lending guidelines require by law that 18% of a bank's credit be directed to agriculture and allied activities. Government of India introduced another set of guidelines that required the banks to open branches in four unbanked locations for every branch in a banked location. This substantially increased the branch network and improved access

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

to finance in rural areas (see Burgess and Pande (2003)). As on 31st March, 2013, there were 157 commercial banks operating 104,467 branches in India.[7]

III.A.4 Poor enforcement

Given state control of banking and the political economy of state controlled lending (see Khwaja and Mian (2005), Cole (2009)), recovery of loans has been a major challenge in India. Though the establishment of debt recovery tribunals and the passage of "Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest(SARFAESI)" Act have substantially improved the NPA scenario (see Visaria (2009), Vig (2013)), neither of them apply to small agricultural loans. Thus, when it comes to agricultural loans, lenders do not have recourse to any special laws and have to rely on courts for enforcement. However, the slow judicial process compounds lenders' difficulties in loan recovery.[8]

III.B Loan Officer Incentives in Indian Public Sector Banks

For employees of public sector banks in India, who are considered as "public servants",[9] the number of years spent on the job remains the most important factor that determines the promotion of a loan officer in Indian public sector banks.

The Ministry of Finance, Government of India decides the compensation for employees of public sector banks; this compensation varies primarily based on the level of an employee in the organizational hierarchy. Unlike their counterparts in the private sector banks, employees in public sector banks do not receive variable pay linked to performance. Moreover, the level of compensation provided to employees of public sector banks is significantly lower than that provided to employees of private sector banks, whose compensation is primarily market-driven.[10] Banerjee, Cole, and Duflo (2008) document that loan officers in Indian public sector banks are driven more by fear of prosecution by the federal vigilance authorities for alleged corruption than by positive rewards related to their performance. Such a skewed incentive structure typically motivates the loan officers to be lax in their effort when the perceived threat of being prosecuted is low. As we argue in section IV, scheduled rotation represents one such instance where the loan officers

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

[8] World Bank's doing business survey 2012-2013 ranks India 132 out of 185 in terms of ease of doing business. In terms of enforcement of contracts India occupies 17th out of 185 countries surveyed. Also, in India it takes on an average 1420 days to enforce a contract. In comparison in Singapore the same takes just 150 days.

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

[10] The Central Bank governor is on record saying that the salaries of public sector executives are far lower compared to the remuneration received by their private sector counterparts. Source: http://profit.ndtv.com/news/market/article-rbi-for-higher-salaries-to-ceos-of-psu-banks-41347 In fact, the chairman of largest bank in India, which is a public sector bank, draws a total remuneration less than 20% of what her counterparts in the private sector draw.

know ex-ante that they cannot be held fully responsible for ex-post loan performance on loans lent towards the end of their tenure.

Indian public sector banks follow a common system of performance appraisal for their employees. As specified in the pro-farma appraisal document issued by the Department of Financial Services, Ministry of Finance, Government of India, a loan officer in a public sector bank in India is evaluated on three dimensions:

1. Business Issues: This category, which gets a weightage of 60%, includes aspects such as lending, NPA management, resource mobilization, selling third-party products such as insurance and mutual funds, income and expense management, etc. These quantitative aspects are measured against set targets.

2. Qualitative aspects: This category includes qualitative aspects such as proper maintenance of books, remarks during audit, compliance of audit instructions, customer service, cleanliness of branch premises, employee satisfaction. Here, the supervising manager decides a rating based on his/her subjective assessment of the employee's performance on these criteria. This category gets a weightage of 10%.

3. Managerial Qualities: In this category, , which gets a weightage of 30%, the loan officer is evaluated for his/her leadership skills, administrative acumen, decision making, communication skills, etc. Here again the supervising manager assigns a score based on his/her subjective assessment of the loan officer.

If a loan officer's performance is rated as below average by the bank, then chances of promotion gets substantially diminished even if the officer has spent many years at the same level. However, a very high rating does not necessarily qualify an officer for promotion unless he/she has spent the required number of years at the particular level of the organizational hierarchy.

From our perspective, a couple of features of the incentives system are worth noting. First, assessment of the loan officers performance is based only by his/her achievements in the current branch. The loan officer's performance in branches he/she previously served has no bearing on his/her current appraisal ratings. The appraisal document only requires the loan officer to provide details about the previous positions held. Second, NPA management receives an overall weightage of only 10%.

IV A Simple Model

We develop a simple model to derive our empirical hypotheses. Consider a principal-agent relationship, where a bank is the principal and loan officer(s) are the agents. We study how the effort choice of the loan officer(s) is affected by job rotation when decision-making inside the firm is driven by soft information. We study this question *given* the

incentive structure set by the principal. Therefore, we take the incentive contract, which the principal decides to incentivize the loan officers, as exogenously given and then examine how job rotation affects the loan officer's effort. Specifically, we assume that the incentive structure is identical across loans that are not affected by job rotation and loans that are affected by job rotation. Apart from our focus being on how effort choice is affected by job rotation, this assumption is justified on conceptual and practical grounds. Conceptually, as discussed in the introduction, when the information collected by the employee is soft, neither the information nor the effort at collecting the same can be verified. In this case, as in Holmstrom and Milgrom (1991) the number of observables—default on the loan in this case—is less than the number of activities performed by two different agents. Therefore, the firm cannot design an incentive contract that rewards each employee partially according to this effort. Moreover, the empirical setting we study—an Indian public sector bank where the incentives are quite low powered—involves a principal that does not alter the incentive structure for loans affected by job rotation vis-à-vis loans that are not affected by job rotation.

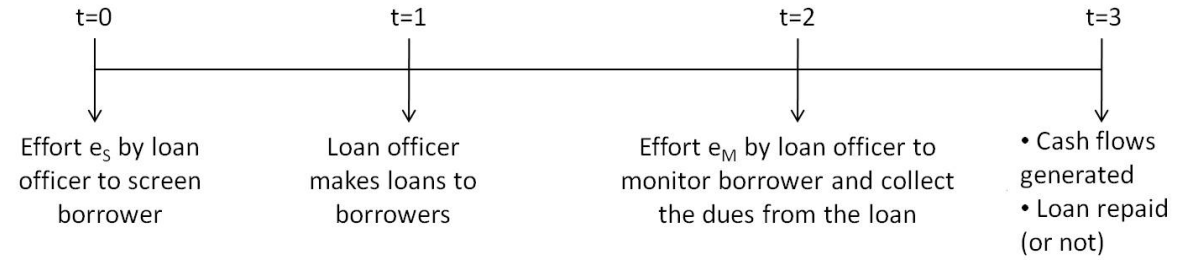

Figure 1: Timing and sequence of events

Figure 1 shows the timing and sequence of events. There are two cash flow dates, $t = 1, 3$ and two dates where effort choices are made, $t = 0, 2$. At date 0, the loan officer invests effort e_S to screen from the pool of potential borrowers to decide the borrowers that receive a loan. At date 1, the loan is made after which at date 2 a loan officer, who could potentially be different from the loan officer that did the screening, invests effort e_M to monitor the loan and to collect the dues from the loan. The loan officer incurs a personal cost of effort which we assume is equal to the level of effort. At date 3, the cash flows from the borrower's project are realized at which point the borrower either repays the loan in full or defaults on the loan.

Greater effort by the loan officer in screening the borrower should reduce adverse selection and thereby the likelihood that a low-quality borrower receives a loan. Similarly, greater effort by the loan officer in monitoring the borrower and then collecting the dues from the loan should reduce moral hazard by the borrower and thereby the likelihood of the borrower defaulting on the loan. We model these effects by assuming that the likelihood of the loan getting repaid in full p increases with the effort in screening e_S and

the effort in monitoring the loan and collecting the dues e_M :

$$\begin{aligned} p &\equiv p\left(e_S, e_M\right), \\ p_i &> 0, p_{ii} < 0, i = 1, 2, \end{aligned} \tag{1}$$

where the subscripts denote partial derivatives. We also assume that the effort in screening and the effort in monitoring and collecting the dues are either complementary to each other ($p_{12} \geq 0$) or substitutes for each other ($p_{12} = 0$):

$$p_{12} \geq 0 \tag{2}$$

Bank lending relies on relationships and soft information (Petersen (2004); Ramakrishnan and Thakor (1984)). In the Indian context, it has been shown that informal relationships between a loan officer and a borrower play a major role in lending and repayment decisions (Fisman, Paravisini, and Vig, 2012). Therefore, the effort invested in screening and monitoring are primarily aimed at collecting soft information about the borrower. Therefore, we assume the effort to be *observable but not verifiable*. This assumption differs from that in Hertzberg, Liberti, and Paravisini (2010), who show that the outgoing loan officer reports truthfully near the scheduled rotation because she fears being exposed by the incoming loan officer. Such exposure is possible when the incoming loan officer can uncover the information the outgoing loan officer chooses to hide. However, uncovering soft information hidden by the outgoing loan officer poses difficulties.

As argued above, we consider incentive contracts for loan officers as exogenously specified. Following the discussion in Section III.B, we model low-powered incentives that reward performance and penalize default:

$$w_p > w_d, \tag{3}$$

where w_p denotes the payoff to the loan officer when the borrower repays the loan in full and w_d denotes the payoff to the loan officer when the borrower defaults on the loan.

IV.A Job Rotation

In a bank, with respect to loans affected by job rotation, the outgoing and incoming officers become jointly responsible for the performance of such a loan. While the outgoing loan officer is responsible for screening and due diligence at the time of lending, the incoming officer bears responsibility for residual monitoring and collecting the dues. This creates a situation of moral hazard in teams (Holmstrom, 1982), where neither the outgoing loan officer nor the incoming loan officer can be held fully responsible for the performance of the loan. We model this by assuming that payoff to the outgoing

loan officer equals $(\alpha \cdot w_p, \alpha \cdot w_d)$ while the payoff to the incoming loan officer equals $([1-\alpha] \cdot w_p, [1-\alpha] \cdot w_d)$, where $0 < \alpha < 1$.

IV.B Analysis

We solve the model by backward induction by considering separately the "job rotation" and "no job rotation" scenarios. First consider the case under "no job rotation." When the loan officer is solely responsible for the performance of the loan and does the screening, monitoring and collection of dues on his own, his expected payoff is given by:

$$U(e_S, e_M) = \underbrace{w_p \cdot p(e_S, e_M)}_{\text{borrower repays loan in full}} + \underbrace{w_d \cdot [1 - p(e_S, e_M)]}_{\text{borrower defaults on the loan}} - e_S - e_M \tag{4}$$

The loan officer decides his screening and monitoring effort to maximize his expected payoff. Using backward induction, given the effort in screening chosen by the loan officer, he chooses monitoring effort to maximize his expected payoff:

$$e_M^{N-JR} = \max_{e_M} U\left(e_S^{N-JR}, e_M\right) \tag{5}$$

where the $N - JR$ denotes effort choice in the "no job rotation" case. The loan officer then chooses screening effort to maximize his expected payoff:

$$e_S^{N-JR} = \max_{e_S} U\left(e_S, e_M^{N-JR}\right) \tag{6}$$

The first-order conditions for the effort choice are therefore given by:

$$p_1\left(e_S^{N-JR}, e_M^{N-JR}\right) = p_2\left(e_S^{N-JR}, e_M^{N-JR}\right) = \frac{1}{w_p - w_d} \tag{7}$$

Now consider the "job rotation" case. As stated above, the outgoing loan officer is responsible for screening while the incoming officer is responsible for monitoring and collecting the dues. Therefore, the expected payoff to the outgoing loan officer U^O is given by:

$$U^O(e_S, e_M) = \alpha w_p \cdot p(e_S, e_M) + \alpha w_d \cdot [1 - p(e_S, e_M)] - e_S \tag{8}$$

The expected payoff to the incoming loan officer U^I is given by:

$$U^I(e_S, e_M) = [1-\alpha] w_p \cdot p(e_S, e_M) + [1-\alpha] w_d \cdot [1 - p(e_S, e_M)] - e_M \tag{9}$$

Given the effort in screening chosen by the outgoing loan officer, the incoming loan officer chooses (monitoring) effort to maximize his expected payoff:

$$e_M^{JR} = \max_{e_M} U^I \left(e_S^{JR}, e_M\right) \tag{10}$$

where the superscript JR denotes effort choice in the "job rotation" case. Anticipating the monitoring effort of the incoming loan officer, the outgoing loan officer chooses effort to maximize his expected payoff:

$$e_S^{JR} = \max_{e_S} U^O \left(e_S, e_M^{JR}\right) \tag{11}$$

The first-order conditions for the effort choice in the "job rotation" case are therefore given by:

$$p_1 \left(e_S^{JR}, e_M^{JR}\right) = \frac{1}{\alpha \left(w_p - w_d\right)} \tag{12}$$

$$p_2 \left(e_S^{JR}, e_M^{JR}\right) = \frac{1}{(1-\alpha) \left(w_p - w_d\right)} \tag{13}$$

IV.C Results

Given these steps for solving the model, we derive the following key results and discuss their testable empirical implications.

Proposition 1. *The efforts in screening, monitoring and collecting the dues are lower for loans affected by job rotation vis-à-vis loans that are not affected by job rotation:*

$$\left(e_S^{JR}, e_M^{JR}\right) < \left(e_S^{N-JR}, e_M^{N-JR}\right) \tag{14}$$

Intuitively, this result is obtained due to the combination of two factors. First, bank lending relies on soft information. Therefore, the incoming loan officer finds it extremely hard to verify the level of effort exerted by the outgoing officer in screening the loan. Similarly, the outgoing officer cannot verifiably prove to his superiors that the incoming loan officer may have exerted low effort in monitoring the loan and collecting the dues. As a result, incentive contracts cannot be based directly on loan officer effort. Thus, incentive contracts have to be based on a verifiable measure such as loan performance. Second, job rotation creates the problem of moral hazard in teams (Holmstrom, 1982). Because neither officer receives *in toto* the marginal benefit/penalty from her effort, the effort by both the incoming and the outgoing loan officers is lower under job rotation than otherwise.

Proposition 2. *The probability of default on loans affected by job rotation is greater than*

on loans not affected by job rotation:

$$p\left(e_S^{JR}, e_M^{JR}\right) < p\left(e_S^{N-JR}, e_M^{N-JR}\right) \tag{15}$$

This result follows from the probability of default on the loan increasing with the effort in screening and the effort in monitoring the loan.

Corollary 1. *The likelihood of the incoming loan officer providing a repeat loan to a borrower screened by the outgoing loan officer is lower than the situation in which the repeat borrower is screened by the same officer.*

This result follows from the incoming loan officer accounting for the possibility that the effort made by the outgoing officer in screening loans (that are affected by job rotation) would be lower than the (screening) effort that she would herself would make in screening the borrowers.

IV.D Empirical Implications

The main empirical implication follows from proposition 2, which implies that loans that are affected by job rotation are more likely to default when compared to loans that are not affected by job rotation. Proposition 1 specifies that the mechanism underlying this effect is that loan officers exert lower effort in screening, monitoring and collecting the dues for a loan affected by job rotation when compared to a loan that is not affected by job rotation. Corollary 1 provides the final empirical implication: because of the lower effort in screening by the outgoing loan officer, the incoming loan officer is likely to ration credit to borrowers that were screened by the outgoing loan officer.

V Data

For our empirical analysis in the paper, we use loan account level information from an Indian public sector bank.[11] The bank provided us data for 15 branches located in four districts in the state of Andhra Pradesh, two districts in Karnataka, and three districts in Maharashtra. The details regarding the names of districts and the location of the branches are provided in Appendix 1. The loan account data provided to us by the bank starts in October 2005 and ends in May 2012. However, as described in the introduction, to avoid the problem of right censoring of data on loan performance for the loans issued later in our sample, we restrict our analysis to loans issued till May 2011.

We have data pertaining to more than 45,000 loans availed by more than 16,000 agricultural borrowers. These loans were issued by 51 different loan officers who managed

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

the 15 branches during our sample period. We obtain information regarding the identity of the loan officer who lent a particular loan and the tenure of the loan officer in a particular branch. We have hand collected this information by verifying bank records. For the purpose of this paper, the loan officer corresponds to the branch manager.

The transaction records provided by the bank include the date of each transaction, a short description of each transaction, transaction amount, type of transaction (debit or credit), the account balance before and after the transaction and type of balance (debit or credit). With help of the account details provided to us by the bank, we are able to infer when a loan was availed, number of days the loan was outstanding, the interest charged etc. All the loans analyzed are crop loans with a one year maturity.[12]

Dependent variable: We define default as the borrower not repaying the loan by the due date of repayment. In using this definition of default, we follow the Reserve Bank of India's guidelines for Asset Classification, Provisioning and Other Related Matters, which stipulate that a loan is considered in default if it has not been repaid by the due date of repayment. Our results remain qualitatively and quantitatively unchanged when we define default as the borrower not having repaid the loan 90 days after scheduled repayment, which corresponds to the Reserve Bank of India's norm for classification of loans into non-performing assets.[13]

Control variables: We use the following controls in our econometric analysis. Rainfall data pertains to district-wise yearly rainfall in the year of loan origination (year hereafter). This data is taken from the Indian Meteorological Department (www.imd.gov.in). Data for direct and indirect agricultural lending and for the total deposits in a (district, year) are obtained from the Reserve Bank of India (RBI) Database on Indian Economy (www.dbie.rbi.org.in). Data for the literacy rate in a (district, year) is obtained from the Indian census data. Inflation is measured as the district-wise yearly consumer price inflation; the data for the same is obtained from the Indian Labour Bureau (www.labourbureau.nic.in). Area of rice production refers to area under rice crop production in '0000 hectares in a year; this data is obtained from the Indiastat database (www.indiastat.com). Yield of food grains is defined as Kg/Hectares yield of all food grain in a year; we obtain this data from www.agricoop.nic.in. Data for the nonperforming assets (NPA) for each year at the country level is obtained from the RBI website. Table 1 provides a brief description of all the variables used in this study.

V.A Descriptive Statistics

Table 2 provides the descriptive statistics for the variables employed in our study. Loan officer tenure equals an average of 809 days, or 2.2 years, while the median equals

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

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

1033 days, or 2.8 years. The probability of default for a loan in our sample, which consists exclusively of agricultural crop loans, is on average 63%. The median loan in our sample does not meet the payment obligations by the scheduled repayment date. While such a large rate of default may be surprising in the context of a developed economy, because of the challenges related to agricultural lending described in section III, high default rates on agricultural loans represent a key concern in developing countries such as India. In fact, concerned with the dismal performance of the agricultural sector and rising farmer suicides because of indebtedness,[14] Government of India set up a high powered committee (The Radhakrishna Committee) in 2007 to study the problem of agricultural distress and high indebtedness and suggest remedial measures. Moreover, as part of the financial budget speech delivered on February 29, 2008, the then Finance Minister of India announced an unprecedented bailout of indebted small and marginal farmers, which increases the rate of default in our sample. However, the empirical strategy we adopt, which exploits staggered transfers of loan officers all through our sample, ensures that the debt waiver scheme does not affect our results.

Table 2 also shows that of the 45592 loans in our sample, approximately 57% (=25976 loans) are given to repeated borrowers. We also notice that on average 30% of the loans are given by a loan officer during the last six months of his/her tenure while the median loan is given earlier. The average loan amount equals INR 59456 or approximately $1000 while the median loan amount equals INR 30,000 or approximately $500.

VI Results

VI.A Empirical Strategy

Our empirical strategy critically depends on loan officer rotation being well-defined and being unrelated to the loan officer's performance. A well-defined loan officer rotation policy also gives an opportunity to the loan officer to plan her moves in advance.

Public sector banks in India follow a uniform policy of rotating their loan officers after three years.[15] Accordingly, the large public sector bank that has provided us with the data follows the same policy. Because the Government of India only issues broad guidelines relating to rotation and promotion of loan officers, banks exercise some discretion in transferring officers before they complete three years or in retaining officers in a branch even after completing three years. Our discussions with the management of the bank

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

[15] 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.

and our review of official documents reveal that administrative exigencies such as acute shortage of officers in a branch/region, death/long illness of a loan officer in a branch, etc. primarily contribute to early transfers (i.e. before completion of three years). On the other side of the spectrum, because a loan officer has to wait for a replacement to be identified and for the replacement to takeover responsibilities from him, which leads to many loan officers' tenure being more than three years.

However, loan officer transfers are unrelated to performance. All officers are members of All India Bank Employees union, which strongly resists any move which is seen by the employees as arbitrary. Due to the potential pressure from the unions, managements of public sector banks play it safe and stick to a uniform transfer policy.

As mentioned in the introduction, in figure 2, we plot the probability of a loan officer continuing in her current job in the $(n+1)^{th}$ month conditional on having been on the job for n months. In this figure, we observe a sharp discontinuity at three years in the probability of a loan officer continuing in her current job. Therefore, we find that the bank's rotation policy of transferring officers after three years is indeed operational on the ground. Figure 3 shows the distribution of loans based on loan officer tenure. We notice here that close to 45% of the loans are originated by loan officers who spend exactly three years in the branch. Moreover, in figures 2 and 3, we find sufficient variation in loan officer tenure around the three-year threshold, which enables us to identify the effect of job rotation on loan performance.

Our empirical strategy also exploits the fact that the sample of agricultural crop loans given by the bank have a fixed maturity of one year, which enable us to cleanly separate officers into "treatment" and "control" groups to estimate the effect of a rotation policy. Using these groups, we estimate a difference-in-difference effect of the rotation policy. To fix ideas, consider a representative loan officer who completes two-and-a-half years in a branch. Because the expected tenure is three years, she can expect to be transferred from the branch in the next six months. So, loans that she originates in the next six months are likely to be due during the tenure of the loan officer that replaces her. Thus, complete responsibility for the performance of the loans that she originates in the last six months of her tenure cannot be attributed to her. Moreover, given the soft information that drives bank lending, the incoming loan officer cannot verify the effort that she made. As a result, this group constitutes the treatment group for examining the effect of job rotation. In contrast, consider a representative loan officer who has not completed two-and-a-half years in the branch. Because she does not expect to be transferred over the next six months, she is likely to be held fully responsible for loans that she originate in these next six months. Such an officer forms part of our "control" group.

We estimate the difference-in-difference as follows. For the treatment group of officers, we first estimate the difference between average default rates for loans originated in the last six months of their tenure vis-à-vis the average default rate for loans originated in

previous periods. Next, we estimate the same difference for the control group of officers. The difference between these two differences provides a causal estimate of the effect of job rotation on loan performance. This is because the second difference provides an estimate for the counterfactual question: what would have been the default rate if the representative loan officer had originated a loan that was not affected by job rotation? To estimate the difference-in-difference, we employ the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{16}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. $Tenure\_30m\_or\_more_i$ is a dummy that takes the value 1 if loan officer i finishes 30 months in the branch and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated in the last six months of the officer's tenure and 0 otherwise. β_i denotes officer fixed effects that enable us to control for the effect of unobserved officer ability on the performance of loans issued by officer i while β_t denotes year fixed effects that enable us to control for time trends in loan performance. The co-efficient β_3 captures the difference-in-difference estimate of the impact of job rotation on loan performance:

$$\begin{aligned} \beta_3 &= (\overline{Y}_{\text{Loans issued in last 6 months}} - \overline{Y}_{\text{Loans issued earlier}})\big|_{\text{loan officers whose tenure} \geq \text{30m}} \\ &\quad - (\overline{Y}_{\text{Loans issued in last 6 months}} - \overline{Y}_{\text{Loans issued earlier}})\big|_{\text{loan officers whose tenure} < \text{30m}} \end{aligned} \tag{17}$$

VI.B Effect of Loan Officer Rotation on Probability of Default

VI.B.1 Basic tests

To examine the effect of job rotation on loan performance, we start by examining the difference in the probability of default between loans issued in the last six months of an officer's tenure and loans issued earlier using the following specification:

$$Y_{ijt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt}$$

We include the following control variables in our tests. First, we include rainfall because it affects the yield of crops. Because the state of Andhra Pradesh, where all the branches in our sample are located, specializes in rice production (the state is called "the rice bowl of India"), all the agricultural loans in our sample are for rice production. Because rice production is significantly influenced by rainfall in the district, we control for the same. Second, we include the following variables measured for the district in which a loan officer's branch is located: (i) the total amount of direct and indirect agricultural lending to control for the demand for agricultural credit in the particular branch, (ii) total deposits to control for the wealth of the district in which the branches located, (iii)

literacy to control for awareness of modern methods of farming that can affect agricultural production, (iv) inflation as it directly affects the borrowers' consumption basket. We also include other control variables that are measured yearly at the country level: (i) total area under rice production, (ii) average yield of food grains, and (iii) total nonperforming assets among agricultural loans.

The results for these tests are presented in table 3. In Column (1), we do not include any control variables except for the year and officer fixed effects. In column (2), we introduce all the district/loan level control variables described above. For brevity, we report the coefficients of log(loan amount) and rainfall in the district because these are the variables that are statistically significant. We find that log(loan amount) is positively correlated with the probability of default, which is consistent with the likelihood of default being greater when the borrower is more indebted. We also find that rainfall in the district is positively correlated with the probability of default. This could possibly be the case because excessive rainfall adversely affects rice production and could therefore lead to borrower distress. In column (3), we include control variables that are measured at the country level: area under rice production, yield of food grains, and agricultural NPA. Because these variables vary at the yearly level, we exclude year fixed effects from the specification though the district/loan level control variables as well as officer fixed effects continue to be included.

Across columns (1)-(3) of table 3, we notice that the coefficient estimate for β_1 is positive and statistically significant at the 1% level. Thus we find that the loans issued in the last six months of and officer's tenure default more than loans issued earlier.

VI.B.2 Difference-in-difference

The above tests do not enable us to control for the effect of confounding factors. For example, the higher default rates in the last six months of an officer's tenure could be because the new officer that replaces him faces a learning curve as in Di Maggio and Van Alstyne (2012). To disentangle the effect of job rotation from this alternative, we employ the empirical strategy using difference-in-difference tests described above.

Because the loan officers in the treatment group can anticipate an impending transfer, they can plan their moves in advance. Loan officers in the control group, who experience unscheduled transfers, cannot do so. Thus, while the effect of the new officer facing a learning curve should manifest in both the control and treatment groups, the effect of job rotation should be visible only in the case of the treatment group. We therefore test equation (25) now; the results for these tests are presented in table 4. The specifications shown in columns (1)-(3) of table 4 are similar to those in table 3.

Across all three specifications, we observe that the coefficient estimate for β_3 is positive and statistically significant at the 1% level, which shows that the difference-in-difference

estimate for the effect of job rotation on the probability of loan default is positive. Economically, using the coefficient estimate for β_3 in column (1) we infer that loans that are affected by job rotation default 7.5% more than loans that are not affected by job rotation.

Across columns (1)-(3) of table 4, we notice that the coefficient estimate for β_2, which provides an estimate of the probability of default for loans originated in the last six months of any officer's tenure vis-à-vis the probability of default for loans originated earlier, is positive and statistically significant at the 5% level or lower in columns 2 and 3. Thus, apart from the difference-in-difference estimate, we find that loans issued in the last six months of an officer's tenure default more often than loans issued earlier.

VI.B.3 Effect of learning

Across columns (1)-(3) of table 4, we notice that the coefficient estimate for β_1 is negative and statistically significant at the 1% level. Thus, the loans originated by loan officers that spend 2.5 years or more in a particular branch have a lower probability of default when compared to loans originated by officers that spend less than 2.5 years in a particular branch. Thus, longer tenure has the overall effect of reducing default rate on loans. As loan officers learn more and acquire soft information about the borrowers, the portfolio quality improves.

VI.B.4 Examining the effects separately for treatment and control groups

In table 5, we examine the effect of job rotation separately for the treatment and control groups. In columns (1)-(3) of table 5, we notice that that the coefficient of the dummy for last six months of tenure is positive and statistically significant at the 1% level. In contrast, in columns 3 to 6 of table 5, we notice that the coefficient of the dummy for last six months of tenure is negative and statistically significant in columns 5 and 6 even though it is insignificant in column 4. Thus, consistent with our hypothesis, job rotation increases the probability of default on loans originated by the treatment group of loan officers. However, consistent with learning on the job, the probability of default on loans originated is lower in the last six months of tenure for the control group of officers.

Also, as we argued in the introduction, the negative coefficients for the control group suggest that the higher default rates observed in table 4 are not due to a new loan officer facing a learning curve as in Di Maggio and Van Alstyne (2012). If that were the case, we should have observed an increase in the default rates in the last six months for the control group as well. Thus, we can infer that the expertise gained on the job reduces default rates for loans issued in the last six months for the control group while the hypothesized effect of job rotation increases the same for the treatment group.

VI.C Disentangling possible effects of hard information

Our hypothesis relies on job rotation leading to lower effort in gathering of soft information by loan officers. As argued in Section III.A, loan officers have to primarily rely on soft information for their lending decisions on agricultural crop loans. Therefore, our empirical setting makes it possible that the above effect of job rotation stems from lower effort in collecting soft information. Nevertheless, we would like to examine further if the above results are indeed stemming from lower effort in collecting soft information. In particular, because default on a loan represents a verifiable outcome and each bank is likely to maintain a record of defaulters, the above results could still be due to the effect of job rotation on collection of hard information. However, if the above effects were due to hard information, then as in Hertzberg, Liberti, and Paravisini (2010), the likelihood of default on loans affected by job rotation should be lower, not higher as we find.

A loan officer does not have to gather any soft information to verify whether or not a loan applicant has repaid the previous loan within the term specified in the contract. To test whether job rotation affects a verifiable measure of loan portfolio quality, we implement the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{18}$$

where Y_{ijt} now measures whether borrower j (to whom loan officer i gave a loan in year t) has defaulted on a previous loan or not. Y_{ijt} equals 1 if borrower j has defaulted on a previous loan and 0 otherwise. By construction, this test is run on the sample of repeat borrowers. The results are presented in table 6. Column (1) shows the results of the specification containing year and officer fixed effects while column (2) shows the results of the specification containing year and officer fixed effects as well as the log of the loan amount. Loan portfolio quality on average improves in the last 6 months of a loan officer's tenure as seen in the negative and statistically significant coefficient estimate for β_2, which suggests that a loan officer is less likely to lend to a previously defaulted borrower in the last six months of his tenure for fear of leaving verifiable evidence of a dubious loan. The coefficient estimate for β_1 is statistically insignificant, which suggests that loan officers in the treatment and control groups are equally likely to lend to previous defaulters.

Crucially, we find that the coefficient estimate for β_3 is statistically insignificant in columns (1) and (2), which suggests that the difference-in-difference estimate for the effect of job rotation on a verifiable measure such as previous default is insignificant. Because the only piece of verifiable information available about the borrower of an agricultural loan is whether or not he/she has defaulted on an earlier loan, the results in table 6 further suggest that job rotation increases the probability of default by reducing effort in

collection of soft information.[16]

VI.D Repeat borrowers versus first-time borrowers

Could it be the case that job rotation adversely affects loan performance by destroying the relationship between the borrower and the loan officer (see Drexler and Schoar (2011) for evidence of such effects)? Because we include officer fixed effects in all our empirical specifications, our tests exploit variation within the loans originated by a loan officer. Therefore, it is unlikely that our results are driven by job rotation destroying the relationship between the borrower and the loan officer. Nevertheless, we examine this alternative thesis using the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Repeated\_Relationship_j + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Repeated\_Relationship_j * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{19}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. $Repeated\_Relationship_j$ is a dummy that takes the value 1 if loan j represents a repeat loan made by loan officer i and 0 otherwise. $Last\_Six\_Months_{it}$ is defined as before.

In table 7, we report the results from testing equation (19). The specifications shown in columns (1)-(3) of table 7 are similar to those in table 3 and in table 4. We observe that the co-efficient estimate for β_1 is negative and statistically significant in all specifications. Thus, borrowers who share a repeated borrowing relationship with the departing loan officer default less, which is consistent with relationship lending reducing the probability of default (Puri, Rocholl, and Steffen, 2010). Because loans given out in the last six months of the outgoing officer's tenure are likely to be affected by job rotation, the coefficient β_2 captures the effect of job rotation for first-time borrowers:

$$\beta_2 = (\overline{Y}_{\text{Loans issued in last 6 months}} - \overline{Y}_{\text{Loans issued earlier}})\big|_{\text{first-time borrowers}}$$

For new borrowers, the loan officer has to make the effort to acquire soft information. The positive and statistically significant coefficient estimate for β_2 shows that job rotation affects the effort by the loan officer to acquire soft information. Interestingly, the coefficient estimate for the interaction term β_3 is statistically indistinguishable from zero. Because loans given out in the last six months of the outgoing officer's tenure are likely

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

to be affected by job rotation, this evidence suggests that the above results are not driven exclusively by repeat borrowers.

Overall, we conclude that the evidence presented in tables 4 to 7 is consistent with our main thesis as predicted by proposition 2.

VI.E Effect Of Loan Officer Rotation On Loan Officer Effort

We now examine attempt to throw some light on this mechanism for the main effect. We use the time elapsed between the date when a loan is repaid by the borrower and the date when he gets a repeat loan. Any delay in renewing the loan can be a measure of (lack of) effort by the loan officer. If it were the result of more careful consideration of the loan application, we should see an improvement in loan performance due to job rotation. In fact, we observe deterioration in loan performance due to job rotation. Therefore, a delay in renewing the loan should proxy for lack of effort.

Of course, we only observe equilibrium outcomes for the number of days elapsed. It is possible that farmers delay their current application because agricultural requirements are seasonal in nature. For example, agricultural activity tends to be lowest during the summer months of April and May. Hence, it is possible that a farmer who repays a loan in March may wait till June before applying for his next loan. To control for such seasonal effects, we can also include fixed effects for the month in which the repeat loan is originated. These fixed effects enable us to control for unobserved differences in the days elapsed depending on the month in which the repeat loan is originated. We therefore implement the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_{month} + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{20}$$

where Y_{ijt} now measures the number of days elapsed between the date when borrower j (to whom loan officer i provides a loan in year t) repaid his/her previous loan and the date when he/she received the new loan. By construction, this test is run on the sample of repeat borrowers. β_{month} captures fixed effects for the month in which the new loan was originated.

The results for this test are presented in table 8. Across columns (1)-(3), we find that the coefficient estimate for β_1 is negative and statistically significant except in column 1, which suggests that loan officers that have a longer tenure in a branch take lesser time to approve the loan for a repeat borrower. Similarly, we find that the coefficient estimate for β_2 is negative and statistically significant in each of the three columns, which suggests that loan officers take lesser time to approve the loan for the repeated borrower in the last six months of their tenure when compared to earlier periods. The negative coefficient estimates for β_1 and β_2 suggests that the loan officer learns on the job and therefore takes

less time to approve the loan for a repeated borrower as his tenure in the branch increases. However, crucially, we notice across columns 1 to 3 that the coefficient estimate for β_3 is positive and statistically significant. The economic effect is large as well: loans that are affected by job rotation take between 32 to 51 days more for approval when compared to loans that are not affected by job rotation, where the mean equals 10 days.

VI.F Effect Of Job Rotation On Possible Credit Rationing

We now test whether job rotation leads to possible credit rationing as implied by Corollary 1, which implies that the incoming loan officer is likely to ration credit to borrowers that had a borrowing relationship with the outgoing loan officer because of lower effort exerted by the outgoing loan officer. We implement the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{21}$$

where Y_{ijt} is a dummy takes a value of 1 if the new loan officer has originated a loan within 182 days (i.e. six months) of loan repayment by previous borrower. Columns (1)-(3) in Panel A of table 9 shows the results of these tests, where the specifications are similar respectively to those in table 3 and in table 4. We notice that the coefficient estimate for β_3 is statistically indistinguishable from zero, which suggests that the difference-in-difference estimate for the effect of job rotation on a new loan being granted is insignificant. Thus, the evidence does not seem to suggest overall credit rationing due to job rotation. We therefore investigate if the new loan officer discriminates between borrowers handled by the outgoing loan officer vis-à-vis other borrowers because the new loan officer may factor in the possibility that the outgoing loan officer may not have invested optimal effort in screening loans given out during the ending period of his tenure. We implement the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Dummy\_loan\_officer\_changes\_after\_disbursement_{ijt} \\ &\quad + \beta_2 * Dummy\_loan\_officer\_changes\_after\_repayment_{ijt} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{22}$$

where Y_{ijt} is a dummy takes a value of 1 if the new loan officer has originated a loan within 182 (i.e. six months) days of loan repayment by previous borrower. Panel B shows the results for testing equation (22). The specifications shown in columns (1)-(3) of Panel B of table 9 are similar to those in table 3 and in table 4.

As evident from results in Panel B, columns (1)-(3), those borrowers that took a loan during the tenure of the previous loan officer and subsequently the loan officer changed before they repaid the loan have 9.6% less likelihood of getting a loan within 6 months of their repayment. Interestingly, the succeeding loan officer is quite unlikely to lend

to those borrowers that received and repaid a loan in the last 6 months of the previous loan officer's tenure. They have a stark 63.5% lower likelihood of getting a loan within next 6 months of their loan repayment. When the new loan officer provides a loan to a borrower that got the loan during the tenure of the outgoing loan officer but repaid during the new officer's tenure, the new loan officer would have spent effort in monitoring this borrower and collecting the dues from the borrower. The new loan officer would not have however screened this borrower. In contrast, when the new loan officer provides a loan to a borrower that got the loan and repaid the loan during the tenure of the outgoing loan officer, the new loan officer has not spent effort on either screening this borrower or in monitoring the borrower. The disproportionately larger effect for borrowers that were screened and monitored by the outgoing loan officer when compared to the effect for borrowers that were screened by the outgoing loan officer but were monitored by the new loan officer is consistent with the predictions in Corollary 1. However, we don't observe overall credit rationing due to job rotation possibly because the new loan officer extends loans to borrowers that were not handled by the outgoing loan officer.

VI.G Robustness

VI.G.1 Threshold Tenure for Classifying into Treatment and Control Groups

In table 10, we examine the robustness of our key by separating loan officers into the treatment and control groups based on whether or not they have completed three years in a particular branch. Because the expected tenure in a branch equals three years, a loan officer that has already spent three years in a branch can be transferred at any point in time. As a result, any loan that such a loan officer originates is likely to be monitored and collected by his/her replacement. Therefore, loans that are originated by loan officers that have spent three years in a branch are at least as likely to be affected by job rotation as loans that originated by loan officers that have spent 2.5 years in a branch. For this purpose, we employ the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_36m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_36m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{23}$$

where the only difference compared with (25) is the use of the $Tenure\_36m\_or\_more_i$ dummy instead of the $Tenure\_30m\_or\_more_i$ dummy. To ensure that there is no other change in our specification, we continue to compare the performance of loans originated in the last six months of tenure vis-à-vis those originated earlier. Columns (1) and (2) of table 10 show the results of testing using equation (23) . Column (1) shows the results of the specification including year and officer fixed effects but without any other control variables while column (2) shows the results of the specification including year and officer

fixed effects as well as other district level control variables. In both these columns, we find that the results are as strong as before.

Next, to examine possible placebo effects that may be accounting for this result, we examine whether the result is obtained when we separate loan officers into treatment and control groups based on whether or not they have completed 1.5 years in a particular branch. Because the expected tenure in a branch equals three years, a loan officer that has only spent 1.5 years in a branch is unlikely to be transferred over the next 1.5 years. As a result, the loan officer is likely to himself/herself monitor and collect any loan that he/she originates in the next six months. Therefore, loans originated in the next six months by loan officers that have only spent 1.5 years in a branch are unlikely to be affected by job rotation. To test for this effect, we employ the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_18m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_18m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned} \tag{24}$$

where the only difference compared with (25) is the use of the $Tenure\_18m\_or\_more_i$ dummy instead of the $Tenure\_30m\_or\_more_i$ dummy. Here as well, we continue to compare the performance of loans originated in the last six months of tenure vis-à-vis those originated earlier. Columns (3) and (4) of table 10 show the results of testing using equation (24) . while the coefficient estimate for β_3 is negative and statistically significant in column (3), it is insignificant in column (4). Thus, when we separate loan officers into treatment and control groups based on a tenure of 18 months, we find that the hypothesized effect of job rotation increasing the probability of default is not obtained. These results Suggest that the above results for the effect of job rotation are not driven by omitted variables that may be leading to some placebo effects.

VI.G.2 Time Varying Unobserved Officer Characteristics

Our causal claims are valid if there are no systematic differences in observable and unobservable characteristics between the treatment and control group of loan officers. Note that all our tests included loan officer fixed effects, which enabled us to control for the effect of time-invarying characteristics of loan officers. However, time-varying loan officer characteristics present a residual concern. Our empirical setting in a public sector bank provides multiple lines of defence against such a concern. First, incentives in public sector banks are low-powered. In particular, loan officers are promoted based on fixed tenure in a particular role and not based on their performance in the role. So, time-varying officer ability is unlikely to correlate with rotation on the job. Second, possible confounding effects created by time-varying officer characteristics require the following high hurdle. Difference in an unobserved characteristic of the treatment group of officers in the last six months when compared to the same characteristic in the previous period

should be systematically different from the identical difference for the control group of officers.

Nevertheless, we test for one possible source of time-varying unobserved officer characteristics. It is possible that the control group of loan officers learn about their impending transfer on promotion at least six months in advance and are thereby motivated to exert more effort. If the same phenomenon manifests for the treatment group of officers as well, then the systematic differences mentioned above would not result. Therefore, for the confounding effects to materialise, lets presume that the above phenomenon affects only the control group of officers and not the treatment group. This unlikely scenario may produce results similar to what we have obtained so far. To rule out this possibility, we rerun our basic difference-in-difference test as in equation (25) by excluding the four officers who were transferred on promotion. The results for this test are displayed in table 11. Our results are unchanged by this exclusion, which addresses concerns that our results are confounded by such time-varying unobserved officer characteristics.

VII Conclusion

In this paper, we show that rotation of agents between tasks leads to costs that have not yet been investigated in the literature. In particular, the *costs* we highlight stem when decision-making inside a firm is driven by soft information because the principal finds it difficult to fix sole responsibility when a task is underatken by multiple agents. Our objective is to highlight a cost of job rotation that should be factored in when analyzing the overall effect of job rotation. Because job rotation can alleviate agency related problems relating to collusion, the ratchet effect, sub-optimal performance, etc. we speculate based on the evidence in this paper that the net effect of job rotation may be positive in organizational settings where hard information is relied upon for decision-making. In contrast, the net effect may be negative in organizational settings where soft information has to be relied upon for decision-making. A fruitful area for further investigation would be to examine how the overall effect of job rotation varies with the structure of information employed for decision-making in a firm.

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Table 1: Variable Description

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

Variable	Description
Probability of Default	1 when the loan has defaulted, 0 otherwise
Log (Loan Amount)	Natural log of loan amount in rupees
Last_Six_Months	Dummy variable; 1 when a loan is originated in last 6 months of tenure of any loan officer, 0 otherwise
Tenure_30m_or_more	Dummy variable; 1 when a loan is originated by a loan officer who has a tenure$\geq$ 30 months, 0 otherwise
Default in Previous Loan	Dummy variable; 1 when the borrower has defaulted in one's previous loan, 0 otherwise
Interval between Loans	Interval between last loan repayment and current loan origination by the borrower in days
Next Loan within 182 Days	Dummy variable; 1 when the next loan is issued within 182 days of repayment of previous loan, 0 otherwise
Rainfall	District-wise rainfall in cm in the year of loan origination (Year)
Additional District-level Controls	**Description**
Direct Agricultural Lending	District-wise direct agricultural lending in '000 crores in the year of loan origination (Year)
Indirect Agricultural Lending	District-wise indirect agricultural lending in '000 crores in the year of loan origination (Year)
Total Deposit	District-wise total bank deposit in '000 crores in the year of loan origination (Year)
Literacy Rate	District-wise literacy rate in percentage in the year of loan origination (Year)
Inflation	District-wise consumer price index in the year of loan origination (Year)
Additional Country-level Controls	**Description**
Area of Rice Production	Area under rice crop production in '0000 Hectares in the year of loan origination (Year)
Yield of Food Grains	Kg/Hectares yield of all food grain in the year of loan origination (Year)
Agricultural NPA	Agricultural NPA in '000 crores in the year of loan origination (Year)

Table 2: Summary Statistics

Our sample comprise of 45592 agricultural crop loans issued by 51 loan officers over the time period October 2005 to May 2011. Of these 45592 loans, 25976 loans constitute repeat loans while the remaining loans constitute first time borrowers.

Variables	No. of Obs.	Mean	Median	Standard Deviation
Loan Officer Tenure (Days)	51	809.10	1033.00	384.74
Probability of Default	45592	0.63	1.00	0.48
Interval between Current and Previous Loan (Days)	25976	50.54	7.00	144.76
Loan Outstanding (Days)	45592	599.37	508.00	467.32
Fraction of Loans issued in Last 6 months of Tenure	45592	0.30	0.00	0.46
Loan Amount (INR)	45590	59456.11	30000.00	1513049.00
Rainfall (cm)	45592	10.00	9.39	3.78
Area of Rice Production ('0000 Hectares)	45592	3557.65	3978.00	1152.52
Agricultural NPA (INR billions)	45592	95.4	71.5	43.5
Yield of Food Grains (Kg/Hectares)	45592	1803.36	1798.00	90.32
Direct Agricultural Lending (INR billions)	45592	7429.0	6097.7	4664.8
Indirect Agricultural Lending (INR billions)	45592	855.0	480.6	717.1
Total Deposits (INR billions)	45592	69877.0	69670.0	44024.0
Literacy Rate (in percentage)	45592	55.94	54.90	6.33
Inflation (Consumer Price Index)	45592	145.36	134.75	26.98

Table 3: Effect of Loan Officer Rotation on Probability of Default

We present OLS regression results for the effect of loan officer rotation on the probability of default using the following specification:

$$Y_{ijt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. The $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Columns (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Columns (3). The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
Dependent Variable	Probability of Default		
Last_Six_Months	0.057***	0.075***	0.113***
	(6.758)	(8.795)	(13.967)
Log (Loan Amount)		0.012***	0.015***
		(4.678)	(5.768)
Rainfall		0.008***	-0.000
		(4.730)	(-0.095)
Constant	0.623***	2.321***	2.731***
	(31.259)	(5.286)	(17.265)
Observations	45,592	45,590	45,590
R-squared	0.290	0.300	0.292
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	NO	YES

Table 4: Difference-in-difference Test for the Effect of Loan Officer Rotation on Probability of Default

We present OLS regression results for the difference-in-difference estimate of job rotation on probability of default using the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. $Tenure\_30m\_or\_more_i$ is a dummy that takes the value 1 if loan officer i (eventually) finishes 30 months in the branch and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3). The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
Dependent Variable	Probability of Default		
Tenure_30m_or_more *	0.075***	0.048***	0.107***
Last_Six_Months	(5.406)	(3.490)	(7.703)
Tenure_30m_or_more	-0.258***	-1.110***	-1.256***
	(-2.931)	(-4.510)	(-9.193)
Last_Six_Months	-0.003	0.036***	0.026**
	(-0.228)	(2.705)	(2.020)
Log (Loan Amount)		0.012***	0.015***
		(4.792)	(6.067)
Rainfall		0.008***	0.001
		(4.890)	(0.441)
Constant	0.885***	3.445***	4.141***
	(9.794)	(5.232)	(17.074)
Observations	45,592	45,590	45,590
R-squared	0.291	0.300	0.293
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	NO	YES

Table 5: Separate Effects of Loan Officer Rotation on Treatment and Control Groups

We report OLS estimates of regressing loan default dummy on the dummy for *Last_Six_Months* of the treatment group, i.e. loan officers who have spent at least 30 months in a particular branch, and the control group, i.e. loan officers who have spent less than 30 months in a particular branch.

$$Y_{ijt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. The $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Columns (1) and (4). We introduce additional district-level controls in Columns (2) and (5) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Columns (3) and (6) of Panel B. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of Default					
	Treatment (Tenure ≥ 30 months)			Control (Tenure < 30 months)		
Last_Six_Months	0.064***	0.076***	0.126***	0.030	-0.137***	-0.091***
	(6.777)	(7.746)	‘	(1.361)	(-6.296)	(-4.054)
Log (Loan Amount)		0.006*	0.010***		0.029***	0.030***
		(1.686)	(3.010)		(6.859)	(7.134)
Rainfall		0.009***	0.001		0.018*	0.071***
		(4.795)	(0.456)		(1.715)	(9.822)
Constant	0.632***	3.921***	3.704***	0.667***	-12.549***	0.509
	(30.952)	(5.665)	(14.023)	(6.814)	(-7.498)	(1.175)
Observations	30,833	30,833	30,833	14,759	14,757	14,757
R-squared	0.180	0.183	0.174	0.492	0.529	0.521
Officer Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	NO	YES	YES	NO
Additional District-level Controls	NO	YES	YES	NO	YES	YES
Additional Country-level Controls	NO	NO	YES	NO	NO	YES

Table 6: Disentangling Possible Effects of Hard Information

To test whether job rotation affects a verifiable measure of loan portfolio quality, we report OLS regression results for the difference in difference estimate of loan officer rotation on the credit worthiness of the loan portfolio, as measured by default in previous loan using the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned}$$

where Y_{ijt} equals 1 if borrower j (to whom loan officer i issued a loan in year t) has defaulted in the previous loan and 0 otherwise. $Tenure\_30m\_or\_more_i$ is a dummy that takes the value 1 if loan officer i (eventually) finishes 30 months in the branch and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Column (1). In Column (2) we use log of the loan amount along with year and officers fixed effects. We do not use any additional controls to avoid look ahead bias. The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)
Dependent Variable	Default in Previous Loan	
Tenure_30m_or_more *	0.023	0.018
Last_Six_Months	(1.218)	(0.950)
Tenure_30m_or_more	-0.014	-0.027
	(-0.133)	(-0.262)
Last_Six_Months	-0.057***	-0.056***
	(-3.555)	(-3.486)
Log (Loan Amount)		-0.018***
		(-5.311)
Constant	-0.038	0.163
	(-0.358)	(1.436)
Observations	25,976	25,974
R-squared	0.255	0.256
Officer Fixed Effects	YES	YES
Year Fixed Effects	YES	YES

Table 7: Performance of Repeated Borrowers in Last Six Months of Tenure

This table reports OLS regression results for the following specification:

$$Y_{ijt} = \beta_0 + \beta_i + \beta_t + \beta_1 * Repeated\_Relationship_j + \beta_2 * Last\_Six\_Months_{it} + \beta_3 * Repeated\_Relationship_j * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt}$$

where Y_{ijt} equals 1 if loan j issued by officer i in year t defaults and zero otherwise. $Repeated\_Relationship_j$ is a dummy that takes the value 1 if loan j represents a repeat loan made by loan officer i and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3). The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
Dependent Variable	Probability of Default		
Repeated_Relationship*	-0.003	-0.002	0.016
Last_Six_Months	(-0.238)	(-0.140)	(1.281)
Repeated_Relationship	-0.079***	-0.086***	-0.085***
	(-9.491)	(-10.318)	(-10.044)
Last_Six_Months	0.064***	0.084***	0.115***
	(7.201)	(9.296)	(13.396)
Log (Loan Amount)		0.016***	0.018***
		(6.603)	(7.576)
Rainfall		0.007***	-0.002
		(4.042)	(-1.007)
Constant	0.630***	1.965***	2.435***
	(32.114)	(4.489)	(14.950)
Observations	45,592	45,590	45,590
R-squared	0.294	0.304	0.296
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	NO	YES

Table 8: Effect Of Loan Officer Rotation On Loan Officer Effort

We present OLS regression results for the effect of loan officer rotation on loan officer effort as measured by time interval between the date when a loan is repaid by the borrower and the date when he gets a repeat loan. We use the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned}$$

where Y_{ijt} measures the number of days elapsed between the date when borrower j (to whom loan officer i provides a loan in year t) repaid his/her previous loan and the date when he/she received the new loan. By construction, this test is run on the sample of repeat borrowers. $Tenure\_30m\_or\_more_i$ is a dummy that takes the value 1 if loan officer i (eventually) finishes 30 months in the branch and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3). All results are The standard errors are clustered at account number level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
	Interval between Last Loan Repayment		
Dependent Variable	and Current Loan Origination		
Tenure_30m_or_more *	51.347***	32.386***	39.540***
Last_Six_Months	(8.633)	(5.089)	(6.866)
Tenure_30m_or_more	-38.398	-468.342***	-254.768***
	(-0.563)	(-4.558)	(-3.147)
Last_Six_Months	-40.480***	-41.011***	-44.177***
	(-8.086)	(-7.583)	(-8.156)
Log (Loan Amount)		-30.396***	-30.531***
		(-17.412)	(-17.589)
Rainfall		3.062***	2.830***
		(5.447)	(4.998)
Constant	-30.574	850.617***	115.257
	(-0.390)	(3.665)	(0.971)
Observations	25,976	25,974	25,974
R-squared	0.153	0.194	0.192
Month Fixed Effects	YES	YES	YES
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	NO	YES

Table 9: Effect Of Job Rotation On Possible Credit Rationing

Panel A: Difference-in-difference

We present the OLS regression results for the difference-in-difference estimate of loan officer rotation on credit rationing as measured by probability of getting the next loan approved within 182 days of repayment of previous loan using the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Tenure\_30m\_or\_more_i + \beta_2 * Last\_Six\_Months_{it} \\ &\quad + \beta_3 * Tenure\_30m\_or\_more_i * Last\_Six\_Months_{it} + \beta X + \varepsilon_{ijt} \end{aligned}$$

where Y_{ijt} is a dummy takes a value of 1 if the new loan officer has originated a loan within 182 days (i.e. six months) of loan repayment by previous borrower. $Tenure\_30m\_or\_more_i$ is a dummy that takes the value 1 if loan officer i (eventually) finishes 30 months in the branch and 0 otherwise. $Last\_Six\_Months_{it}$ is a dummy that takes the value of 1 for loans originated by loan officer i in year t if these loans were originated in the last six months of her tenure and 0 otherwise. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3).The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
	Probability of Getting		
Dependent Variable	Next Loan within 182 Days		
Tenure_30m_or_more *	-0.004	0.000	-0.008
Last_Six_Months	(-0.852)	(0.000)	(-1.544)
Tenure_30m_or_more	0.044	-0.234**	0.305***
	(0.942)	(-2.562)	(4.487)
Last_Six_Months	0.009**	0.004	0.016***
	(2.003)	(0.904)	(3.473)
Log (Loan Amount)		-0.004***	-0.004***
		(-4.079)	(-3.408)
Rainfall		0.001	0.001
		(1.640)	(1.156)
Constant	0.974***	2.388***	0.711***
	(20.649)	(10.002)	(6.525)
Observations	45,592	45,590	45,590
R-squared	0.084	0.086	0.085
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	YES	NO

Panel B: Discrimination Against Borrowers Handled by the Outgoing Loan Officer

In Panel B, we present OLS regression results for the effect of job rotation on the new loan officer discriminating between borrowers handled by the outgoing loan officer vis-à-vis other borrowers. We use the following specification:

$$\begin{aligned} Y_{ijt} &= \beta_0 + \beta_i + \beta_t + \beta_1 * Dummy\_loan\_officer\_changes\_after\_disbursement_{ijt} \\ &\quad + \beta_2 * Dummy\_loan\_officer\_changes\_after\_repayment_{ijt} + \beta X + \varepsilon_{ijt} \end{aligned}$$

where Y_{ijt} is a dummy takes a value of 1 if the new loan officer has originated a loan within 182 (i.e. six months) days of loan repayment by the same borrower. $Dummy\_loan\_officer\_changes\_after\_disbursement_{ijt}$ takes a value of 1 if the outgoing loan officer changes after loan disbursement and $Dummy\_loan\_officer\_changes\_after\_repayment_{ijt}$ takes a value of 1 if the outgoing loan officer changes after repayment. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3). The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)
	Probability of Getting		
Dependent Variable	Next Loan within 182 Days		
Dummy for Loan Officer Changes	-0.096***	-0.097***	-0.095***
After Disbursement	(-31.311)	(-31.643)	(-31.231)
Dummy for Loan Officer Changes	-0.635***	-0.637***	-0.636***
After Repayment	(-30.421)	(-30.683)	(-30.527)
Log (Loan Amount)		-0.004***	-0.003***
		(-3.665)	(-2.827)
Rainfall		0.003***	0.001*
		(3.772)	(1.693)
Constant	1.037***	2.146***	0.875***
	(124.379)	(12.980)	(16.341)
Observations	45,592	45,590	45,590
R-squared	0.191	0.194	0.192
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional Controls	NO	YES	YES

Table 10: Robustness of Difference-in-difference Result

We present robustness of the difference-in-difference estimate using two different cut-offs for tenure to define treatment and control groups. The regression specification is similar to that employed in Table 4. In Columns (1) and (2), treatment and control groups are based on whether or not loan officers have completed three years in a particular branch. In Columns (3) and (4), treatment and control groups are based on whether or not loan officers have completed 1.5 years in a particular branch. No controls except year fixed effects and officer fixed effects are used in Column (1) and (3). We introduce additional district-level controls in Column (2) and (4) along with year fixed effects and officer fixed effects. The standard errors are clustered at each borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

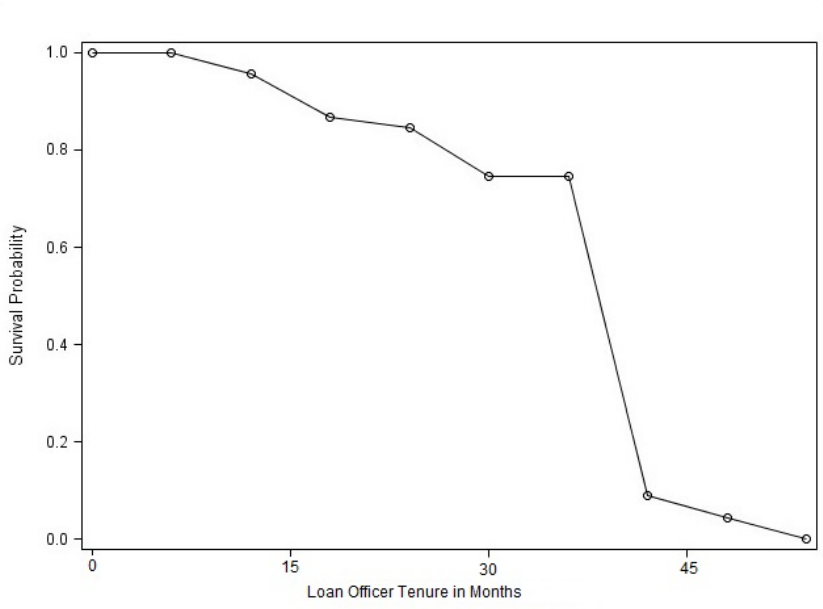
	(1)	(2)	(3)	(4)
Dependent Variable	Probability of Default			
	Tenure Cutoff m=36 Months		Tenure Cutoff m=18 Months	
Dummy for Loan Officer Tenure ≥ m months * Last_Six_Months	0.075***	0.048***	-0.120***	0.002
	(5.406)	(3.490)	(-3.968)	(0.050)
Dummy for Loan Officer Tenure ≥ m months	-0.258***	-1.110***	-0.096**	-1.081***
	(-2.931)	(-4.510)	(-2.438)	(-4.589)
Last_Six_Months	-0.003	0.036***	0.169***	0.074**
	(-0.228)	(2.705)	(5.708)	(2.460)
ln_loan		0.012***		0.012***
		(4.792)		(4.670)
Rainfall(D)		0.008***		0.008***
		(4.890)		(4.714)
Constant	0.885***	3.445***	0.719***	3.402***
	(9.794)	(5.232)	(18.358)	(5.165)
Observations	45,592	45,590	45,592	45,590
R-squared	0.291	0.300	0.291	0.300
Officer Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Additional District-Level Controls	NO	YES	NO	YES

Table 11: Effect of Loan Officer Rotation on Probability of Default after Excluding Officers who are Transferred on Promotion

We present OLS regression results for the difference-in-difference estimate of job rotation on probability of default after excluding officers who are transferred on promotion. The regression specification is similar to that employed in Table 4. No controls except year fixed effects and officer fixed effects are used in Column (1). We introduce additional district-level controls in Column (2) along with year fixed effects and officer fixed effects. Year fixed effects are excluded and country level controls are introduced in Column (3). The standard errors are clustered at borrower level and adjusted t-statistics are reported in parentheses below the regression estimates. ***, **, * represents statistical significance at the 1%, 5% and 10% levels.

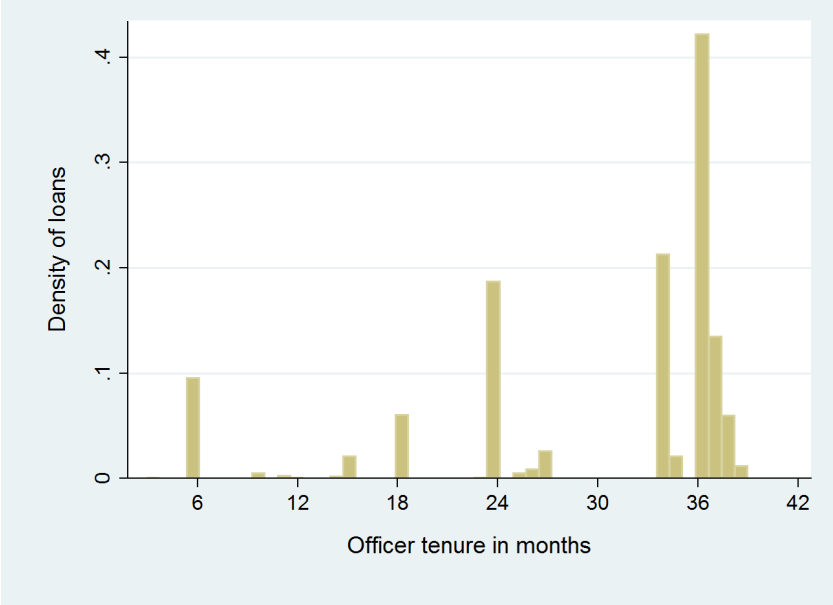
	(1)	(2)	(3)
Dependent Variable	Probability of Default		
Tenure_30m_or_more *	0.111***	0.159***	0.170***
Last_Six_Months	(6.927)	(8.814)	(10.846)
Tenure_30m_or_more	-0.200**	1.708***	-1.665***
	(-2.252)	(5.416)	(-11.246)
Last_Six_Months	-0.050***	-0.085***	-0.047***
	(-3.240)	(-4.936)	(-3.082)
Log (Loan Amount)		0.008***	0.011***
		(3.022)	(4.321)
Rainfall		0.001	-0.002
		(0.517)	(-1.071)
Constant	0.820***	-3.811***	5.387***
	(8.976)	(-4.502)	(19.573)
Observations	40,946	40,944	40,944
R-squared	0.268	0.280	0.273
Officer Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	NO
Additional District-level Controls	NO	YES	YES
Additional Country-level Controls	NO	NO	YES

Figure 2: Kaplan-Meier survival curve with Loan Officer Tenure in Months



Note: The graph shows Kaplan-Meier survival curve (also known as the Kaplan-Meier product limit estimate) against loan officers tenure (in months). The discontinuity in the graph occurs at 12_th quarter which illustrates that the average loan officer gets transferred after 3 years.

Figure 3: Histogram of Loan Disbursal Density with Loan Officer Tenure in Months



Note: The graph shows loan disbursal density against loan officers tenure in months.

Appendix A - Proofs

Consider the following first-order conditions for efforts e_S and e_M :

$$p_1(e_S, e_M) = \frac{1}{x} \tag{25}$$

$$p_2(e_S, e_M) = \frac{1}{x} \tag{26}$$

Differentiating (25) and (26) with respect to x, we obtain:

$$p_{11}(e_S, e_M)\frac{de_S}{dx} + p_{12}(e_S, e_M)\frac{de_M}{dx} + \frac{1}{x^2} = 0 \tag{27}$$

$$p_{21}(e_S, e_M)\frac{de_S}{dx} + p_{22}(e_S, e_M)\frac{de_M}{dx} + \frac{1}{x^2} = 0 \tag{28}$$

Solving the above expressions, we obtain:

$$\frac{de_S}{dx} = \frac{p_{12} - p_{22}}{x^2(p_{11}p_{22} - p_{12}^2)} > 0; \frac{de_S}{dx} = \frac{p_{12} - p_{11}}{x^2(p_{11}p_{22} - p_{12}^2)} > 0 \tag{29}$$

because $p_{12} > 0, p_{11} < 0, p_{22} < 0$ and $p_{11}p_{22} - p_{12}^2 > 0$ from concavity of p. Now comparing (7) with (12) and (13), because $\alpha < 1$, it follows that $\left(e_S^{JR}, e_M^{JR}\right) < \left(e_S^{N-JR}, e_M^{N-JR}\right)$. Then, using $p_1 > 0$ and $p_2 > 0$, it follows that $p\left(e_S^{JR}, e_M^{JR}\right) < p\left(e_S^{N-JR}, e_M^{N-JR}\right)$. Moreover, from (9), we have $\frac{dU^I}{dp} = (1-\alpha)(w_p - w_d) > 0$ because $\alpha < 1$ and from (3) $w_p > w_d$. Now, because $p\left(e_S^{JR}, e_M^{JR}\right) < p\left(e_S^{N-JR}, e_M^{N-JR}\right)$, $U^I\left(e_S^{JR}, e_M^{JR}\right) < U^I\left(e_S^{N-JR}, e_M^{N-JR}\right)$. Therefore, the likelihood that the IR constraint for the new officer would be satisfied is lower under job rotation than under no job rotation, which leads to Corollary.$\diamond$

Appendix B - Location of Bank Branches

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