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How Organizational Hierarchy Affects Information Production

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Abstract

This paper empirically investigates how organizational hierarchy affects the allocation of credit within a bank. Using an exogenous variation in organizational design, induced by a reorganization plan implemented in roughly 2,000 bank branches in India during 1999-2006, and employing a difference-in-differences research strategy, we find that increased hierarchization of a branch decreases its ability to produce "soft" information on loans, leads to increased standardization of loans and rationing of "soft information" loans. Furthermore, this loss of information brings about a reduction in performance on loans: delinquency rates and returns on similar loans are worse in more hierarchical branches. We also document how hierarchical structures perform better in environments that are characterized by a high degree of corruption, thus highlighting the benefits of hierarchical decision making in restraining rent seeking activities. Finally, we document a channel – managerial interference – through which hierarchy affects loan outcomes.

Keywords: Hierarchies, Soft Information, Banks, Globalization, Complexity

JEL Classification: D21, D83, G21, G30

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1 Introduction

Over recent years, there has been a substantial change in the landscape of lending, with banks becoming larger, more globalized, and more complex (Mester, 2012; Herring and Carmassi, 2012). While it is understood that banks benefit from economies of scale, it is argued that hierarchical structures may be inferior when it comes to granting loans to small and medium size enterprises (Stein, 2002; Aghion and Tirole, 1997). Given the importance of small and entrepreneurial firms for innovation and economic growth, it is plausible that the shift towards hierarchical organizations hampers growth. Furthermore, by favoring borrowers that have hard information, such as an established credit history, and depriving borrowers that lack such information, the change in the organizational structure of banks may perpetuate inequality in society. In this paper, we examine how organizational hierarchy affects the allocation of credit.

There is now a growing recognition that organizational design matters. However, despite the abundance of theoretical literature on this topic, empirical research has been rather scant. Two obstacles hinder empirical research in this area. The first impediment comes from the paucity of good micro-level data. A researcher not only needs detailed data on the organizational design of firms, but also requires comprehensive information on outcome variables, to identify the effect of changes in organizational design. The second problem relates to the classic endogeneity problem. Even if one is fortunate enough to get access to organizational-level micro data, one still has to grapple with the fact that the choice of organizational design is not random. While cross-sectional studies are informative about the plausible relationship, they are plagued by the problem of omitted variables. To make any causal claims, the researcher has to seek some exogenous variation in the organizational hierarchy.

In this paper we use micro-level data from a large bank in India with roughly 2,000 bank branches, to examine how organizational hierarchy affects the information that banks produce on loans that they originate. The dataset not only offers comprehensive information on financial contracts of individual borrowers, but also micro-details on the organizational design of all branches of the bank. Most importantly, we have both time series and cross-sectional variation in the organizational design variables of branches, which allows us to utilize the within-branch variation in organizational design for identification. More specifically, the identification strategy exploits changes in organizational design, brought about by a bank-level, pre-determined reorganizational rule (discussed in Section 3), and employs a difference-in-differences (DID) research design to investigate how hierarchies affect information production on loans.

We find that organizational hierarchy affects both the quantity and the quality of loans originated by banks. Specifically, we observe that an increase in hierarchy results in a 9.9 percent decline in total new loans issued by the bank branch and a 5.4 percent decline in the average loan size. Furthermore, we find that an increase in organizational hierarchy leads to a 4.5 percent reduction in the number of small retail borrowers. On examining the performance of these loans, we find that there is a substantial drop in the quality of loans originated. Delinquencies on loans in more decentralized branches are 30 percent lower, and a similar loan portfolio in the decentralized branch generates a 15 percent higher return for the bank. More importantly, the effects are greater when we examine value-weighted, instead of equally-weighted, defaults and returns. This differential effect implies that decentralized structures appear to allocate credit more efficiently. We show that none of the results are driven by pre-treatment trends.

Our results are consistent with better information being produced on loans in more decentralized structures and provide support for incentive-based theories on organizational design (Stein, 2002; Aghion and Tirole, 1997). To further sharpen our analysis, we examine the second moment of contract terms on loan agreements similar in spirit to Rajan et al. (2015). They argue that more information should increase the variance of the contract terms, as it allows banks to discriminate amongst borrowers. Consistent with this prediction, we find that a new layer in the hierarchy reduces the variance of contract terms (e.g., loan size), suggesting that an increase in hierarchy reduces information generated on loans.

A noteworthy feature of our setting is that larger and more hierarchical structures are headed by more senior officers, who have the discretion to approve higher loan amounts. If a borrower requests a loan above the cut-off limit of a given branch, their application is automatically sent to a higher level office at the regional level.[1] Clearly, an increase in organizational level implies that certain loans that would otherwise have been sent to a more senior branch are now approved within the lower branch. On examining these 'large' loans that can be approved in the branch after the change, we find that the branch issues more of them and generates more soft information on them. Given that these loans underwent a reduction in hierarchical distance, the result provides additional support for the view that an increase in organizational hierarchy reduces the information produced on loans. Nevertheless, by evaluating the combined retail

[1]For this reason, in our main specifications, we investigate only those retail loans that can be approved by the lowest rank officer within all branches.

portfolio, we find that the gains in large loans do not offset the losses on small loans.

Our results can be rationalized using the Aghion and Tirole (1997) framework. Delegation of decision-making to the agent gives the agent greater initiative, but results in a loss of control for the principal. In hierarchical structures, this delegation is not completely credible – the principal cannot commit not to intervene with the agent. This lack of delegation of authority – principal interfering in agent's decision making – reduces the agent's incentives to exert effort. Fortunately, our data allows us to examine the interference channel in more detail. Specifically, we have loan-level information on the extent of intervention. Consistent with Aghion-Tirole's framework, we find that managers intervene in decision making of the junior manager in more hierarchical branches. Moreover, we find that the effects of hierarchy are stronger in branches that have a higher degree of intervention, suggesting that managerial interference, which translates into lower autonomy of the agent, is the prime mechanism at work.

Next, we investigate how organizational hierarchy interacts with corruption. Delegation in the presence of corruption may be a double-edged sword (Tirole (1986); Banerjee et al. (2013)). On the one hand, if an agent's private benefits are aligned with those of the principal, then delegation may create an extra incentive to perform the task. On the other hand, if those benefits are not aligned, it may be worthwhile maintaining control over the employees. To understand how organizational hierarchy interacts with rent-extraction, we compare the effects in more corrupt states to those in less corrupt ones. We proxy for corruption by focusing on branches in the so-called BIMARU states (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh) which have been singled out for corruption (Kumar, 2007). Our estimates indicate that for corrupt states, the effects of hierarchization are significantly reduced, thus highlighting the benefits of hierarchical structures in mitigating corruption.

We also examine the effect of bank competition on our results and find several noteworthy patterns. While our results are present across the spectrum of bank competition, they are particularly noticeable in more competitive banking markets. One plausible mechanism through which the costs of hierarchy are amplified in competitive markets is adverse selection. As competitive markets offer borrowers more and possibly better choices, an inferior contract, offered by a hierarchical bank, would induce the good borrowers to switch in such a market. This, however, generates a portfolio that has been adversely selected for hierarchical banks. In a monopolistic setting, however, the borrowers have little choice, so while banks lose out on some profits,[2] the

[2]The reduction in soft information reduces the ability of a monopolist branch to extract surplus.

adverse selection is less severe.

We have so far argued that a change in organizational design affects only the hierarchy of decision making. However, it is plausible that other contemporaneous changes may have affected lending. As a first check, we control for local shocks to credit demand and competition among others by using interacted quarter-district fixed effects. In this way, we exploit the within-district variation, and show that all our results remain qualitatively unchanged. Furthermore, an increase in the hierarchy of a branch brings in a higher level officer. To the extent that the higher level officer has different ability and experience, this may confound inference. Clearly, higher ability on the part of the loan officer would generate the opposite results, whereas lack of local expertise would deliver similar results to those we document here. We address this concern by showing that changing branch manager while keeping the organizational design fixed does not deliver any results. By exploiting manager-specific style (or manager fixed effect) and showing that the results are alleviated in branches where managers intervene less, we identify directly the incentive-based mechanism, as proposed by Aghion and Tirole (1997). We carry out many other robustness tests and discuss some alternative stories in Section 7. Overall, the results provide strong support for the view that organizational hierarchy affects banks' ability to produce information.

This paper adds to the literature on organizational hierarchy and information production (Aghion and Tirole, 1997; Stein, 2002).[3] These theories analyze the trade-off involved in delegating decision-making to the agent. On the one hand, delegating a task leads to increased initiative on part of the agent. On the other hand, it exposes the principal to a potential conflict of interest – the agent may choose a project that could hurt the principal. An important insight from this theory is that the likelihood of interference dulls the agent's incentives to exert effort. In the context of banking, these theories argue that hierarchical organizational structures are ill-suited for producing subjective (i.e., 'soft') information on loans. Confirming the theoretical predictions, our results suggest that the lower effort, induced by the hierarchical organizational design, leads to greater standardization of loans and rationing of "soft information" loans. Furthermore, this standardization leads to a reduced loan performance.

Our work also adds to existing empirical literature on organizations, particularly banks, and their design. A large stream of literature argues that as banks become larger and organizationally complex, they decrease lending to retail customers and small businesses, borrowers being

[3]See also the "communication costs" based theories à la Garicano, 2000.

particularly dependent on subjective information.[4] In particular, our work is closest to Liberti and Mian (2009), Canales and Nanda (2012), Qian et al. (2015), and Liberti (2005), who show that more hierarchical organizational structures tend to rely more heavily on hard, factual information about the borrower. What is unique about our approach is that we use shocks to the organizational design and observe the effect on the information that a bank produces on similar loans before and after the treatment. Moreover, our data records whether a branch manager intervened with a loan decision, allowing us to identify directly the incentive-based (e.g., Aghion and Tirole, 1997; Stein, 2002) rather than communication cost (e.g., Garicano, 2000) theories through which organizational hierarchy affects production of information.[5] To the best of our knowledge, this is the first paper to identify a precise channel that leads to a reduction in soft information due to organizational hierarchy. Furthermore, we provide new insights by highlighting some of benefits associated with hierarchies in corrupt areas and costs in competitive areas.

Our paper also contributes to the literature on distance in credit markets. These studies argue that the proximity between the borrower and the lender mitigates the information asymmetry (Petersen and Rajan, 1995, 2002; Degryse and Ongena, 2005; Mian, 2006; Liberti and Mian, 2009; Alessandrini et al., 2009; Agarwal and Hauswald, 2010; Fisman et al., 2012; Brown et al., 2012; Berg et al., 2013). The key distinction here is that we focus on hierarchical distance, as opposed to geographical distance (Petersen and Rajan, 1995) or cultural distance (Fisman et al., 2012).

The rest of the paper is organized as follows. In the next section, we begin by providing an overview of the data and a description of the institutional details of the Indian bank that we study. In Section 3, we present the baseline empirical specification for the analysis. Section 4 describes our results on lending quantity and loan performance; Section 5 shows the results on soft information; Section 6 discusses results on large loans, managerial intervention, corruption, and bank competition; and Section 8 rules out a range of alternative explanations. Section 9

[4] Some of the most notable works include Berger and Udell (1995); Berger et al. (1995, 1999); Strahan and Wetson (1998); Berger et al. (1998, 2001); Cole et al. (2004); Degryse et al. (2009); Liberti et al. (2012). A somewhat related work by Karpoff (2001) analyzes the incentive effects by comparing public vs. privately funded Arctic explorations. He finds that privately funded expeditions performed better partly because they adopted nonhierarchical organizational structures.

[5] Another notable contribution is by Berger et al. (2005), who argue that usage of soft information is negatively associated with size of a bank. A conjecture behind their empirical strategy is that bank size is a good proxy for organizational design. In this respect, the key advantage of our paper is the ability to differentiate between organizational design and size effects. Therefore, we can nail down the effects induced by organizational hierarchy and protect ourselves against a potential capture of a spurious correlation.

concludes our study.

2 Data

The data for this study comes from a large, state-owned Indian bank operating over 2,000 branches that are geographically dispersed across India (Figure (1)). The dataset is rich in detail. It contains detailed information not only on all loan contracts, but also on the organizational design of all of the bank's branches.[6] At the contract level, it includes the loan balance outstanding, the interest rate, the maturity, the type of collateral, the collateral value, and the number of days late in payment, among other information. On the organizational front, it provides us with vital information on the number of managerial layers in each branch office, the overall seniority of the branch, the loan limit of the branch manager (which is linked to his seniority), and some other discretionary powers of the branch manager. Furthermore, we have information on the extent of branch manager's intervention with the loan decisions. The sample spans 29 quarters – 1999 Q1 to 2006 Q1.

2.1 Loans and Borrowers

We focus on first-time, individual (retail) borrowers. During our sample, the bank issued 1.75 million such contracts. For the purposes of this study, we aggregate the loan-level information and obtain 54,079 branch-quarter observations. In Table (1), we present means, medians, standard deviations, and the 1st and the 99th percentile for the main variables of interest. The loan amounts are expressed in rupees.[7]

In a quarter, the average branch lends to 24 new retail borrowers with a mean loan size of 56,000 rupees, which is roughly 1,300 USD. Furthermore, the equally-weighted delinquency rate, defined as 60 or more days late in repayment within a year since the origination of the loan, is 5.0 percent. In comparison, the value-weighted delinquency rate is only 4.2 percent, suggesting that larger debt is less likely to be late in repayment and is issued to better quality borrowers. In addition, the average rupee-weighted return on loans is 7.0 percent. Moreover, 90 percent of all loans are secured with a median ratio of collateral to loan value of 1.42. Lastly, the average maturity and interest rate are 4.2 years and 11.4 percent, respectively.

[6] Due to confidentiality reasons we are unable to disclose the exact number of branches.

[7] The average exchange rate during our sample period was 0.022 USD per rupee.

2.2 Organizational Design

Figure (2) provides an illustration of the managerial hierarchy of the bank. In total, there are eight management levels. Employees in each layer are comparable in terms of their responsibilities, discretionary power, experience, and salary. The top five layers, starting with *Assistant General Manager,* constitute the senior management team and are mainly involved in business development. The lower ranked employees consist of junior managers, senior managers and chief managers who focus more on the operation side of lending as managers in branch offices. Every ranked employee has a credit origination limit, and that limit increases with the rank of the official.

The organizational chart of the bank is as follows (see Figure (3)). The Chairman and the Executive Directors of the bank operate from the central office and set all bank-wide policies, which are then executed in other lower level branches. Below the central office there are zonal offices, which represent distinct geographical zones across the country. Within each zone, there are several regional offices that are responsible for business development in different regions of a zone. Finally, under each regional office, there are a large number (2000+) of *standardized* branch offices, headed by different level officers.

With regard to the organizational design of branches, the branch head can be seen as the chief executive of the branch: she is responsible for the whole business of the branch, within the policy guidelines that are set by the central office. The branch manager can decide on whether to grant a loan and has considerable discretion over the terms of the loan contract, with the exception of the interest rate, which is set by the central office. For instance, all home improvement loans have the same interest rate as car loans with a maturity of up to five years (for an example, see Table (A1) in Appendix A). It should be noted that while the lower level loan officers in a branch can approve loans that are within their approval limit, the branch manager has the formal authority to overrule those decisions, if he sees fit. As a general rule, the larger the branch, the more senior the rank of the official who heads it. In total, there are three branch structures (see Figure (4)). The smallest branch (level 1) is typically headed by a branch manager, the next branch up (level 2) is headed by a senior branch manager, and finally the branch on level 3 is overseen by a chief manager. Higher level branches have more layers of hierarchy associated with them. For example, level 1 branches generally have only one additional layer (loan officers), and the branch manager directly interacts with the borrowers.

However, a level 3 branch would have three layers: loan officers, managers, and senior managers.

The lending process is relatively simple (see Figure (5)). The borrower approaches the bank and fills in the application form. The application may be rejected by the loan officer, which ends the whole process. If not, the loan officer evaluates the loan application to assess the borrower's credit risk. The loan officer and the borrower then meet to discuss the needs, collateral requirements and other possibilities. Once a loan officer and a borrower agree on the loan terms, the loan is approved by the loan officer if the agreed size of the loan falls within his discretionary powers. If the loan exceeds the loan officer's approval limit, it goes to the next authority up for approval. If the requested loan is even above the discretionary powers of the branch manager, the loan application, along with the branch's assessment, is forwarded to a more senior manager in either regional, zonal, or central office. Nevertheless, the decision on whether to reject the application or send it for approval outside the branch remains with the head of the branch.

Table (2) reports cross-sectional summary statistics. More hierarchical branches originate larger loans, serve fewer customers, and their loan book performs better, as measured on the basis of both delinquencies and returns. That said, it should be noted that these cross-sectional patterns may be driven by the heterogeneity in types of borrowers in different branches, or by the degree of bank competition. For instance, higher-level branches may be located in areas with more economic activity and a lower borrower risk profile. Thus, to alleviate these concerns, we exploit within-branch changes in organizational design, allowing us to control for such cross-sectional differences.

2.3 Employee Incentives

Loan officers and managers are evaluated annually, based on a range of criteria. These include quantitative measures such as the amount and profitability of lending, as well as qualitative considerations such as employee skill development and effective customer communication. Each officer is ultimately assigned a numerical grade from zero to one hundred. While there is limited incentive pay, officers are motivated through possible promotion to a higher rank manager position. Whether an officer or a manager is nominated for a promotion depends on their annual evaluation, including the profitability of issued loans, and their tenure at the bank. A promotion is generally accompanied by a transfer to a new branch.

3 Empirical Specification

Our identification strategy employs a branch restructuring policy that is driven by pre-defined rules. A given branch is upgraded (downgraded) if over the last two years, the average outstanding balance of the combined loans and deposits exceeds (falls below) a fixed cut-off point. In the event of an upgrade, a branch is allocated more resources, including more personnel to meet the rising demand for services in that district, and vice versa. To manage the larger workforce, the branch's organizational hierarchy is also adapted by adding an additional layer of managers (see Figure (6)). In addition to those changes, the approval limit of the head of the branch is increased. Thus, while the organization is more hierarchical after the reorganization, it gets more resources and discretionary power. During our sample period, a total of 500 (roughly a fifth) of all branches were reorganized (see Figure (7)).

We wish to highlight a few points about the reorganization of branches. Firstly, these cut-offs were fixed in the central office by a new CEO of the bank, before the start of our sample. Thus, from the perspective of a single borrower, the organizational design of a branch is exogenous. Secondly, we would like to stress again that we are examining the loans that are eligible for internal approval within all branches, that is, we are looking at loans that are lower than 500,000 rupees (approx. 11,000 USD). This allows us to analyze a similar set of loans across all types of organizational designs, ensuring that the approval limit does not interfere with the loan decisions. It is important to emphasize that most of the branches that we examine have loan approval limits that are significantly above this cut-off (more than double), so this constraint is not binding for most of the loans that we examine.

Our empirical strategy attempts to identify the effect of organizational hierarchy on the parameters of interest (e.g., soft information, delinquencies, or return on loans). We employ a difference-in-differences (DID) strategy and compare branches that were subject to a change in their organizational design against a control group of branches that were not affected by these reorganizations. Thus, the empirical specification is given by:

$$y_{bq} = \tau_q + \tau_b + \delta \text{Branch Level}_{bq} + \eta_{bq}, \tag{1}$$

where the dependent variable (e.g., soft information) is measured at the branch-quarter level; q and b index the quarter and the branch, respectively. *Branch Level*$_{bq}$ stands for the organizational design of branch b in quarter q. It is a variable between one and three, where the lowest and highest values describe decentralized and centralized (i.e., four-layer) branches, respectively. The branch fixed effects (τ_b) absorb any time invariant branch characteristics. The quarterly dummies (τ_q) control for aggregate time trends. This strategy identifies the effect of organizational structure on the production of information and the consequent outcomes, controlling for time and branch invariant effects. The coefficient δ is our DID estimate of the effect of organizational design on, e.g., the production of soft information. Our identification strategy assumes that the variation in the organizational design is plausibly uncorrelated with local developments, allowing us to make causal inferences of organizational design on loan outcomes. We will revisit this identification assumption later in the paper, where we explicitly show that controlling for local-shocks (for example, demand shocks) non-parametrically by adding district interacted with quarter fixed effects does not affect our results.

The identification approach can be understood using the following example. Let us suppose that there are two branches, branch A and branch B, both undergoing organizational change, but one in 2000 and the other in 2004. We wish to estimate the effect of the upgrade on production of soft information. For branch A, we would compare the measure of soft information after 2000 with the one before 2000. However, in 2000 other considerations, such as the economic environment, may have affected the quality of soft information. Branch B, as a control group, would help to control for changing economic conditions. The difference of these two differences would then serve as our estimate of the organizational effect on the production of soft information. Essentially, branch B, which undergoes a change in organizational design in 2004, acts as a control group for branch A until 2004. It should be noted that the staggered nature of organizational shocks implies that all reorganized branches belong to both treated and control groups at different points in time. Therefore, equation (1) implicitly takes as a control group all branches that are not subject to reorganization at quarter q, even if they have already been reorganized, will be reorganized later on, or will not be reorganized at all.

4 Results

4.1 Lending

We begin by reporting the effect of the organizational design on new credit quantities in columns 1 to 3 in Table (3), estimated using the difference-in-differences methodology (specification (1)). The estimated coefficient of interest is the one on *Branch Level*, a variable between one and three where one stands for a decentralized branch and three for a centralized one. Both columns include quarter and branch fixed effects. We find that an increase in organizational hierarchy reduces the total lending to new borrowers by 9.9 percent (column 1) and the number of new borrowers by 4.5 percent (column 2). The difference between the two values implies that the average loan declined by 5.4 percent (column 3).

We have so far assumed that the change in organizational design affects only the supply side of the loan granting process. However, it is plausible that our results are driven, for example, by local, contemporaneous demand shocks or changes in the degree of bank competition. To account for these and other similar concerns, we saturate our main specification by including interacted quarter with state, region and district fixed effects.[8] The finest specification with quarter-district fixed effects splits our sample into 362 geographical districts and controls for all time variation within those districts (on average there are 7 branches in a district). As a result, we exploit the within-district variation between treated and non-treated branches. To the extent that local shocks affect all branches at a district level, such shocks get differenced out in our specification. As columns 4 through 6 show, saturating the specification does not affect the qualitative nature of our results.

In columns 7 through 9, we further investigate issues of other contemporaneous events. One concern might be that, as the branches grow over time, the effect on loan quantities is a branch-specific time trend rather than a hierarchy-induced phenomenon. We can address this and similar other concerns by studying the dynamic effects of organizational change on loan quantities. We replace the *Branch Level* with four variables to track the effect of organizational design before and after the change: Before^2 is a dummy variable that equals one (minus one) for a branch that will be upgraded (downgraded) in one or two quarters; Before^0 is a dummy variable that equals one (minus one) if the branch is upgraded this quarter or one quarter ago; After^2 is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago; and After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four or more quarters ago. The variable Before^2 allows us to assess whether any quantity effects can be found prior to the change. Finding a significant effect could suggest that our results are driven by factors other than organizational design. In fact, the estimated coefficient on the Before^2 is economically small and statistically insignificant.

[8] We report the most stringent specification that includes quarter-district fixed effects. The results are qualitatively the same, using the weaker two specifications – interacted state-quarter and region-quarter fixed effects.

Furthermore, we find that the coefficient on the Before^0 is smaller than those on the After^2 and After^{4+}, suggesting that the documented effect continues in the long run.

4.2 Loan Repayment

As highlighted above, if organizational hierarchy induces information frictions, then this loss of information should be reflected in lower loan quality. To show this, we examine the effect of organizational hierarchy on future loan repayment by estimating specification (1). We classify loan as delinquent if it is more than 60 days past due within a year. As before, we aggregate the loan level default measure and obtain a branch-quarter delinquency rate.

We find that an increase in hierarchy increases loan delinquencies. The coefficients on the *Branch Level* in Table (4) are economically large and statistically significant at 1 percent, for both equally- and value-weighted default rates in columns 1 and 2, respectively. The absolute increase of value-weighted default rates is 1.4 percent, implying a 33 percent increase in the default relative to the mean value-weighted default rate of 4.2 percent. In comparison, the effect on the equally-weighted measure is 1.0 percent, corresponding to a 20 percent increase relative to the mean. Moreover, the effects remain strong after controlling for local demand shocks through quarter-district fixed effects (column 3). Most importantly, we find a significant difference between the estimated value- and equally-weighted measures (column 4). That means that in a centralized structure not only the pool of loans deteriorates (increase in equally-weighted rates), but also more money is allocated towards bad borrowers within this pool (even higher value-weighted rates). This evidence is consistent with the view that an increase in hierarchy reduces banks' ability to produce information on loans, thus impairing a branch's ability to allocate resources efficiently. As such, this differential effect on default rates is enough to say that information is lost in line with Aghion and Tirole (1997) and Stein (2002). Finally, the dynamic effects of the change in organizational design (columns 5 and 6) indicate that there is no sign of a pre-trend two quarters prior to the change.

4.3 Return on Loans

So far, we have shown that more centralized organizational hierarchy leads to lower lending quantities and worse ex-ante capital allocation, as measured by loan delinquencies. Even though the default rates go up, the effects on monetary returns are unclear. On the one hand, increasing default rates put a downwards pressure on the returns. On the other hand, factors such as the recovery rates might alleviate these effects on returns.

To investigate the effects on monetary returns, we measure the return on the portfolio of loans (ROL) originated at the branch b in the quarter q. First, we calculate the lifetime ROL for each loan separately, and only then do we aggregate the loan-level returns at the branch-quarter level. The return on loans, representing bank earnings per rupee lent during the lifetime of a loan, is given as follows:

$$\mathrm{ROL}_{b,i,q} = \sum_{\tilde{q}=q}^{\hat{q}} \omega_{b,i,\tilde{q}} \left[(1 + r_{b,i,\tilde{q}}) \left(1 - \mathbb{1}_{60+_{b,i,\tilde{q}}} \right) + \mathbb{1}_{60+_{b,i,\tilde{q}}} \rho_{b,i,\tilde{q}} \right], \quad (2)$$

where $\omega_{b,i,\tilde{q}} = \frac{\mathrm{Loan}_{b,i,q}}{\sum_{\tilde{q}=q}^{\hat{q}} \mathrm{Loan}_{b,i,\tilde{q}}}$ is the value-weighted component; $r_{b,i,\tilde{q}}$ is the quarterly interest rate; $\mathbb{1}_{60+_{b,i,\tilde{q}}}$ is a dummy variable equal to one if the loan is 60+ days late in the repayment; $\rho_{b,i,\tilde{q}}$ is the expected return in case of delinquency; q is the quarter of the origination of the loan; $\hat{q}$ is the quarter when the loan is repaid in full, the loan is 60+ days late, or the last quarter in our dataset (whichever comes first). By weighting each quarter with the outstanding loan amount instead of equal weights, we place more emphasis on the quarters when the cash flows of the loan contribute more to the branch's performance, i.e., when the outstanding loan amount is higher. Moreover, if a loan defaults towards the end of the repayment period, when only a fraction of the loan remains unpaid, we do not overestimate the effect of the loss given default. All in all, the value-weighted ROL is a better measure for estimating the impact on a branch's performance than the equally-weighted measure.

When a loan becomes delinquent, the expected return is given by the following identity:

$$\rho_{b,i,\tilde{q}} = \eta_{age_i} \cdot \delta_{\{s,u\}} + (1 - \eta_{age_i}) (1 + r_{b,i,\tilde{q}}), \quad (3)$$

where η_{age_i} is the estimated value-weighted default probability, conditional on the age when the loan becomes 60+ days delinquent; $\delta_{\{s,u\}}$ is the value-weighted recovery rate from the defaulted loans, computed as the value recovered against the defaulted principal and interest due for secured (s) and unsecured (u) loans separately.

To account for censoring in our data (i.e., not all loans are repaid or default by the end of Q1:2006), in the last quarter of the dataset we calculate the expected return on a loan in the following way:

$$R_{b,i,\bar{q}} = (1 - \sigma_{age_i}) (1 + r_{b,i,\bar{q}}) + \sigma_{age_i} \cdot \delta_{\{s,u\}}, \quad (4)$$

where σ_{age_i} is the transition probability for a healthy loan, or one that is less than 60 days late, to default eventually by loan age; $r_{b,i,\tilde{q}}$ and $\delta_{\{s,u\}}$ are the quarterly interest and the recovery rates, respectively. We then replace the term in the square brackets in the equation (2) with the one calculated here ($R_{b,i,\bar{q}}$) for all healthy loans in Q1:2006. Lastly, the estimated default probabilities, required for computing the return on loans, are plotted in Figure (8).

The estimated value-weighted recovery rate for individual secured loans is 40 percent, while for unsecured loans it is only 16 percent, reflecting the importance of the realization value of the collateral when seized in default (see Table (5)). Our average estimated recovery rate is similar to the 25 percent provided by the Doing Business database from The World Bank (2013).

Since the dataset does not provide the recovery values for any of the loans that default prior to the first quarter of 2006, we calculate the recovery rates using the data from the last quarter (Q1:2006) of our sample only. As we may be overestimating or underestimating the recovery rates,[9] for robustness we also check our results using three other recovery rates:[10] 25 percent as suggested by the Doing Business Database of the World Bank, a pessimistic 15 percent and an optimistic 50 percent. Qualitatively, the results remain the same.

We find that the return on the same set of loans decreases after a branch becomes more hierarchical (Table (6)). The point estimates suggest that after the introduction of an additional managerial layer, the value-weighted return on an individual loan decreases by 100 basis points (column 2). The economic effect is considerable. Given that every quarter the bank earns 7.0 percent on every rupee lent (the value-weighted return), the 100 basis point decline is equal to a 14 percent drop from the mean return. Similarly, for the equally-weighted measure, the 70 basis point fall in return (column 1) is equivalent to a 10 percent slip in the branch's performance. Further, the estimated results remain unchanged after controlling for local demand shocks through quarter-district fixed effects (column 3) and do not have any pre-trend (columns 5 and 6), therefore ruling out reverse causality concerns. Last but not least, analogous to the delinquency result, the significant difference of 30 basis points between rupee- and equally-weighted measures (column 4) further supports the argument that hierarchy leads to frictions in information production. The returns on large loans shrink more than on the small

[9]For example, in June 2002, the government of India improved creditor rights by enacting the Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest Act. In a nutshell, this act allows banks and financial institutions to auction properties (residential and commercial) when borrowers fail to repay their loans. As it enables banks to reduce their non-performing assets (NPAs) by adopting measures for recovery or reconstruction, we may be overestimating the recovery rates before 2002.

[10]The results are available upon request.

ones, suggesting that resources are allocated less efficiently in the more hierarchical structure.

The results so far support the view that an increase in organizational hierarchy reduces banks' ability to produce information and affects their credit allocation. The differential effect on equally- and value-weighted defaults and returns is enough to conclude that information is lost in more hierarchical organizations, as predicted by incentive-based theories (Aghion and Tirole, 1997; Stein, 2002). In further sections, we provide additional evidence to support this.

5 Alternative Approach

In this section, we sharpen the evidence that organizational hierarchy leads to loss of information by showing that contracts are more standardized in a centralized structure. To capture the soft information content in loans, we use methodology similar in spirit to the procedure employed in Rajan et al. (2015).

Consider two borrowers with identical hard information, but differing in soft information content. A loan officer who has no information about the borrowers would give similar loan contracts to each of these borrowers (a pooled contract). On the other hand, a loan officer who has perfect information would be able to discriminate between the borrowers by giving, for instance, a higher loan amount to the good borrower and a lower to the bad one, all else equal. Thus an increase in information would be captured in an increase in dispersion of contract terms. This is the basic intuition behind the test. In a world with no information, all the variance in quantity (dependent variable) would be explained by the variance in hard information variables (independent variables). However, in a world with perfect information, there would be some variation in contract terms that would not be captured by hard information variables – the lender uses the soft information to discriminate against borrowers who have similar hard information. Thus, if a decentralized organization were closer to the world with perfect information, the variation, unexplained by hard information, ought to be higher.

To estimate the effect of organizational design on information production, we use two approaches. In the first one, we evaluate the second moment of the loan quantity, assuming that the latent demand remains constant. Given that the other contractual terms did not change, tracking the evolution of the second moment over time would allow us to analyze the changes in the soft information component. In the second approach, we relax the assumption that other loan characteristics have not changed and employ a "quasi" R-square analysis similar as in Rajan et al. (2015).

5.1 Variance in Quantity

In the first approach, we exploit two measures that have been used in the literature to capture soft information through variation in loan quantity: inter-quartile range and standard deviation of debt (see, for instance, Fisman et al. (2012). Both measures possess similar characteristics: the larger the amount of soft information, the larger the proxy. Using the difference-in-differences methodology defined in specification (1), qualitatively, both measures deliver the same result: contracts become more standardized when a branch is converted to a more hierarchical unit (see Table (7)). The inter-quartile range of debt (column 1) and standard deviation of debt (column 2) decrease by 12.3 and 9.5 percent, respectively. Furthermore, these effects remain unchanged from a qualitative point of view after absorbing all local shocks through quarter-district fixed effects (columns 3 and 4). Lastly, in columns 5 and 6, we investigate the dynamic effects and find no pre-trend. In fact, if anything, both pre-trend coefficients show the opposite signs. Moreover, all of the effects increase over time and persist in the long run.

5.2 "Quasi" R-square

For the second approach, we use a two-stage estimation procedure. Given that small borrowers are credit constrained in India (see, for example, Banerjee et al. (2005)), we can estimate the bank's credit supply curve. Thus, in the first stage, using the loan-level data, we regress the quantity of loans granted to the borrower against several hard information variables and obtain the equilibrium supply schedule. This gives us a mapping from characteristics to the quantity of the loan supplied by the bank. We then use this model to generate the predicted value based on the characteristics of the borrower. The difference between the actual and the predicted value (i.e., the error term) gives us a measure of soft information content on the loans. We then calculate the standard deviation of these error terms and scale it by the variance of the dependent variable to generate a "quasi" R-square. The higher the soft information, the lower the measured R-square.

More specifically, to measure the soft information, we take the residual $\hat{\epsilon}_{biq}$ from the following regression:

$$y_{biq} = \tau_q + \tau_b + \theta' X_{biq} + \epsilon_{biq}, \tag{5}$$

where i denotes a borrower, q denotes a quarter, and b is a branch. The dependent variable y_{biq} is the natural logarithm of the loan outstanding at the quarter of origination. The log transformation of the loan size reduces its skewness and allows coefficients to be interpreted as elasticity. The two fixed effects - τ_b and τ_q - capture the time invariant components of each branch and aggregate time-series shocks to all branches, respectively. X_{biq} is the vector of control variables. The vector of controls includes contract-specific characteristics, such as maturity, value of the collateral, gender, and product group fixed effects.

Table (8) examines the relationship between the loan amount and borrower characteristics (variables that capture hard information) for new individual borrowers, as defined in equation (5). As can be seen, the higher the value of the collateral, the larger the loan amount. Specifically, raising the collateral by 10 percent would increase the loan amount by roughly 1.6 percent. Similarly, the longer the maturity, the larger the loan size. Additionally, female borrowers, representing 17 percent of the sample, take loans that are, on average, 10 percent smaller than those taken by male borrowers. The adjusted R^2 of the regression is 0.55. This leaves 45 percent of the credit model unexplained, therefore implying that the bank's credit decisions are based on roughly 45% subjective information.

In graph-form, we find that hierarchical branches are associated with less soft information. Figure (9) plots the kernel density functions of soft information for decentralized and centralized branches.[11] For the most hierarchical branches, the measure of soft information is more centered around the mean (zero) than for the more flatly organized branches, implying less variation in subjective information. The Kolmogorov-Smirnov test for the equality of distributions claims that the two density functions differ with a 1 percent significance level.

More formally, Table (9) measures the outcomes at the level of branch b in quarter q. Columns 1 to 4 evaluate the cross-sectional patterns. The first column reports the results, using the quarter fixed effects only. In the other specifications, we also control for geographic characteristics, such as differences in dominant industries or institutional development. Thus, in addition to the

[11] The residuals are standardized to account for the heterogeneity in the pool of borrowers across branches. For a better understand of why this is, imagine the following situation. The distribution of granted loans in branch A is wide (i.e., large standard deviation) due to significant heterogeneity in the borrower's requirements. On the other hand, the distribution of granted loans in branch B is narrow (i.e., small standard deviation). However, the estimated residuals in both cases are the same. Judging by the residuals, both branches would look alike, but this is not the case. As the variation in errors is the same, while the variation in the dependent variable is larger for branch A, the model's predictive power for branch A is higher than for branch B (think in terms of R^2). Consequently, as the R^2 for branch A is higher, it would imply loans being more standardized there. Therefore, for cross-sectional analysis, we scale the residuals for each branch by the standard deviation of the dependent variable - natural logarithm of the loan size. Please note that the scaling does not affect the results in the DID specification as the branch fixed effects implicitly account for the branch invariant characteristics such as clientele.

quarter effects, column 2 controls for the zone-specific trends, whereas column 3 controls for the regional trends. Finally, besides the regional and time trends, in column 4, we also control for all unobservable characteristics of branches with the same initial organizational design (i.e. the one we observe at the beginning of the sample).

Cross-sectional analysis suggests that flatter and less hierarchical branches are associated with additional soft information. All four specifications give strong, negative results, statistically significant at 1 percent. The magnitudes imply that an additional managerial layer is associated with roughly 7 percent lower production of soft information when measured against the mean soft information.

To alleviate concerns about the omitted variable bias that confounds cross-sectional analysis, we turn to our main DID specification, defined in equation (1). As the choice of the organizational design is endogenous to the firm, it might be that the captured correlation in the cross-sectional results is driven by a firm-specific or clientele-specific effect, rather than by organizational design. Studying the same set of loans before and after the reorganization, we find that they become more standardized in a more hierarchical structure (column 5 in Table (9)). The estimated coefficient on the *Branch Level* is negative and significant at 1 percent. In terms of economic magnitudes, the introduction of an additional managerial layer increases the contract standardization by roughly 5.3 percent when measured against the mean soft information. Furthermore, the results remain qualitatively the same after absorbing all local shocks through quarter-district fixed effects (column 6). Hence, the agency problems between the manager of the branch and the loan officer are strong. These two findings again confirm that a hierarchical structure leads to distortions in information production.

Figure (10) plots the dynamics of soft information around the branch reorganization that are estimated after controlling for branch and quarter fixed effects. The figure investigates issues of other contemporaneous events that might be driving the contract standardization and hence the change in the organizational design. As can be seen, there is no pre-trend and the results intensify over time. Column (7) of Table (9) reports the same result more formally. The estimated coefficient on the Before^2 is economically small and statistically insignificant, meaning that there is no pre-trend in the data. Furthermore, the coefficient on the Before^0 is smaller than those on the After^2 and After^{4+}, suggesting that the loan standardization amplifies over time and remains significant.

5.3 Hard Information and Default Predictability

A conjecture we are making thus far is that hierarchy leads to a loss of soft information. In this section, we provide additional support for this. Clearly, if soft information is valuable, then decentralized branches should rely less on hard information in their loan decisions. Exploiting the methodology by Rajan et al. (2015), it is possible to explore the predictive power of hard information. Specifically, hard information should be a a better predictor of loan performance in hierarchical branches than in decentralized ones. Put it in econometric context, the "R-square" of regressions explaining loan performance ought to be higher in hierarchical offices.

To explore this, we evaluate how well hard information predicts future defaults in more hierarchical branches as compared to decentralized ones. We estimate the following logit expression

$$\mathrm{P}[Default_{it} = 1] = \Phi\left(\alpha + X'\theta\right) \tag{6}$$

where the dependent variable is a dummy variable equal to 1 if the loan is more than 60 days past due within a year and zero otherwise. Vector X contains hard information such as loan-to-value ratio, maturity, interest rate, etc. depending on the specification, described in detail in the notes of Table (10). R-square of this specification is the variable of interest.

As often all loans are repaid in full, making the dependent variable equal to 0, we run this specification at a district-quarter-hierarchy level.[12] Thus, for each quarter-district we will have an R-square estimate for all decentralized branches (level 1) to all hierarchical branches (level 3), in total three observations. Then, in the second stage, we compare whether the R-square is higher in more hierarchical branches, controlling for all time varying district-specific characteristics through interacted quarter-district fixed effects. As expected, we confirm that hard information does predict future defaults better in more hierarchical branches (Table (10)).

[12] In an ideal case, one would run such a specification for each branch-quarter separately and extract the R-square of the model. However, doing this at the branch-quarter level is infeasible – often there is no variation in defaults (dependent variable) at the branch-quarter level, as all loans are repaid in full. In such case, we would be left with 10,000 branch-quarter observations (i.e., where we get a Pseudo-R2). As a result, we do not get sufficient number of observations for each branch to exploit the within-branch variation using the difference-in-differences methodology.

6 Other Results

6.1 Trade-off: Large Loans

One of the rationales for the bank's policy towards changing the organizational design of a branch is to increase the within-branch discretionary power and therefore allow more loans to be approved internally. In this way, the bank hopes to shorten the processing time and to gather more information for borrower assessment. After centralizing a branch, the distance between the borrower and the decision maker increases for small loans. But the opposite is true for the loans that were above the approval limit of the branch and had to be approved externally before the upgrade.[13] If the information argument is true for small loans, it must also hold for the larger ones. Thus, large loans should benefit from the upgrade, as the manager can now decide about the loans internally. Identifying the same mechanism for large loans supports our results on small loans.

Since after an upgrade the head of a branch can act on soft information, we find an improvement in the lending outcomes on large loans (see Table (11)). Firstly, to capture the effect on the total debt granted, we use $\ln(1 + Debt)$ as the dependent variable (column 1). The log transformation reduces the skewness and adding one to all values ensures that quarters without loans do not become missing values. Secondly, the effect on the large loan extensive margin, i.e., the probability that a large loan is granted, is captured by a linear probability model (column 2). Thirdly, as the average number of 'large loans' per branch-quarter is 1.4, computing the second moment of the residual as the measure for soft information becomes challenging, if not impossible. Therefore, we use the mean absolute value of the residual estimated in specification (5) (column 3). The properties of this measure are similar to the main proxies of soft information: the larger the amount of soft information, the greater the mean absolute value. We test this proxy in our main results on small loans and find the same results in qualitative terms. As the results for small loans are qualitatively the same for all measures of soft information, we conjecture that the same must hold true for large loans.

The estimated coefficients on the *Branch Level* are positive and significant across all three specifications. The estimates imply that lending of large loans increases when the approval of these loans is carried out internally (column 1), and the probability of issuing a large loan

[13] Formerly a loan application had to be sent to a regional, zone, or head office, where another manager would evaluate the application based on the material submitted.

increases by 3.3 percentage points (column 2). The latter result is equivalent to a 21 percent increase in the average probability of issuing a large loan. The soft information increases as well (column 3). To address the reverse causality, we also show the dynamic effects. None of the estimated effects have a pre-trend. In fact, the effects increase over time and remain significant in the long run.

Although small loans suffer from the hierarchy, the very large borrowers, who, in terms of physical distance, are closer to the decision maker after a branch is centralized, benefit from the proximity. Thus, while a branch might be losing on the small loans, it could recover the loss through gains from the large loans. Therefore, we examine how organizational hierarchy affects the combined retail portfolio that includes both small and large loans.

We find that when a branch is upgraded the gains on large loans are not sufficient to cover the losses that a branch makes on the small loans. In the combined retail portfolio, the default rates increase and returns decrease (columns 4 and 5 in Table (12)), while the lending volume remains unchanged (column 6). We also find that the loan contracts are more standardized (columns 1 through 3). Thus, the overall effect on the retail portfolio remains negative.

6.2 Hierarchy and Corruption

Full delegation in the presence of corruption is a double-edged sword (Tirole (1986); Banerjee et al. (2013)). On the one hand, if the private benefits of an agent are aligned with those of the principal, then delegation may be a good idea, as it creates an extra incentive to perform the task. For instance, Bandiera et al. (2009) show that giving more discretion to bureaucrats in Italian public procurement may lead to budget savings, even though it allows the bureaucrat to pocket some of the money. On the other hand, if agent's private benefits are not aligned with the profit-maximizing behavior of the principal, it may be worthwhile maintaining control over the employees. For example, by analyzing regulators, Stigler (1971) and Leaver (2009) argue that discretion may lead to outcomes that reflect regulators' personal objectives, rather than the social objectives that give raise to regulation in the first place. Essentially, the nature of corruption determines the optimal level of discretion.

To understand how organizational hierarchy interacts with rent-extraction in our setting, we compare the effects in more corrupt states to those in the less corrupt ones. We proxy for corruption by focusing on branches in the so-called BIMARU states (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh) which have been singled out for corruption (see, for example, Kumar (2007)). Our estimates indicate that for BIMARU states, the effects are significantly reduced (see Table (13)). We find similar results using alternative corruption proxy – BIMAROU – which adds the state of Orissa to the BIMARU list. These findings are in line with the view that greater delegation provides extra incentives to generate 'soft' information, while simultaneously enabling rent extraction. However, if the decision making were centralized in the corrupt branches, the benefits of limiting corruption might be attenuated by the incentive problems and the consequent loss of 'soft' information.

6.3 Competition

Finally, we examine how our results vary with the degree of bank competition. Theoretically, the effect of competition is ambiguous, making it an empirical question. We measure branch competition as the log of the total number of branches per 1,000 inhabitants at a district level. The number of branches per district is obtained from the website of the Reserve Bank of India and the number of inhabitants per district from the India Census, both from 2001.[14] We then interact the measure with our organizational design variable (Branch Level) and obtain an estimate that describes the effects of upgradation in more competitive areas (i.e., more branch offices per 1,000 inhabitants) compared to less competitive areas.

We present our results in Table (14). While our results are present across the spectrum of bank competition, they are all – soft information, returns, defaults and quantities – particularly strong in more competitive banking markets (see Table (14)). The results suggest that, in competitive markets, a sub-optimal organizational structure produces the biggest losses for the bank. One plausible mechanism through which the effects are amplified in competitive markets is adverse selection. While more hierarchical banks produce less information, borrowers have more and possibly better choices in competitive markets. Thus, borrowers switch if offered inferior contracts, generating a portfolio that has been adversely selected. In a monopolistic setting, however, the borrowers have little choice, so while banks lose out on some profits, the adverse selection is less severe. Our results add to the findings of Canales and Nanda (2012) who find that decentralized banks are more sensitive to external factors in competitive areas.

[14]We would like to thank Shawn Cole for providing us with this data.

7 Interpretation of the Mechanism

We have so far documented that hierachization of branches results in reduction of soft information production. We next explore the channel that delivers this result. Aghion and Tirole argue that threat of managerial interference is what leads to the underprovision of effort by the agent. Fortunately, our dataset allows us to investigate this channel more precisely, as we observe the extent of managerial interference in a branch at the loan level.

Using this data, we find that an increase in hierarchy leads to more managerial interventions (see Table (15)). We find that the fraction of loans that are approved by the junior manager (the manager with the smallest approval limit) shrinks by 6 percent in a more hierarchical branch (column 1). Furthermore, we also find that the effects of hierarchy are amplified in branches that have higher degree of managerial intervention (columns 2, 3, and 4, respectively).

While these results suggest a possible association between the degree of interference and information production, it raises a natural question: what drives the intervention? We find that managerial style is an important determination of this intervention. Some managers by nature intervene more and this managerial fixed effect explains some of the variation in the data. It should be noted that the analysis is similar in spirit to the manager style literature (see, for example, Bertrand and Schoar (2003) and Graham et al. (2012)).

To put this in our context, it is reasonable to expect that some branch managers are more likely to delegate loan applications than others. To show that this is the case in our setting as well, we estimate the manager's type and show that the performance of a branch improves when lead by a manager who intervenes less.

We estimate the manager style as follows. The decision on whether or not to delegate a loan application can be expressed by the following identity:

$$\text{Delegate}_{bmi} = \tau_b + \tau_m + \epsilon_{bmi}, \tag{7}$$

where m stands for a manager, b for a branch and i for a borrower. Delegate_{bmi} is a dummy variable equal to 1 if the manager m of the branch b decides to delegate the loan application of the borrower i to a junior manager and zero otherwise. The branch fixed effect – τ_b – captures the branch-specific time invariant propensity to delegate, as some branches may be located in areas where intervention is more necessary, for instance, more corrupt areas. τ_m is the branch manager fixed effect and ϵ_{bmi} is mean zero noise term. After estimating the average probability to delegate in each branch, we can compute the manager style, i.e. a manager's individual propensity to delegate:

$$E\left[\tau_m\right] = E\left[\text{Delegate}_{bmi} - \tau_b\right].$$

Using our estimates of managerial style, we analyze how this style interacts with the performance of a branch. For this, we exploit the manager rotation policy and run a second regression

$$y_{bq} = \tau_b + \tau_q + \delta \hat{\text{Delegate}}_{bq} + \epsilon_{bq}, \tag{8}$$

where $\hat{\text{Delegate}}_{bq}$ is the managerial fixed effect, estimated using equation (7): $\hat{\text{Delegation}}_{bq} = \hat{\tau_{mbq}}$ – propensity to delegate by a manager m who is located at the branch b in the quarter q. We find that the a branch performs better when lead by a manager whose style is to delegate more (see Table (16)). These findings are strong both cross-sectionally (columns 1 through 4) and within the same branch after controlling for branch and time fixed effects (columns 5 and 6). Overall, these results provide strong evidence in support of Aghion and Tirole's theory that the possibility of intervention adversely affects incentives to exert first-best effort.

8 Discussion

We have so far shown that a change in organizational design affects a bank's ability to produce information on loans and has implications for capital allocation decisions by banks. We have also identified an incentives-based channel that drives these results. This section addresses a few more items that could potentially confound our inference.

8.1 New Officer Effect

A change in organizational design also brings in a new official as the head of the branch. If the branch gets upgraded to a higher level, it brings in a more experienced and senior official to head the branch. One would expect that the presence of an experienced official should improve the credit allocation decision in the bank because the loan officer, approving loans earlier, now has access to a more knowledgeable advisor. It should be noted that such an effect, if present, would lead to increased soft information and lower defaults on loans, thus biasing against finding the result that we have identified in the paper.

In a similar vein, one could argue that the arrival of a new branch manager leads to a temporary loss of information by so inducing the poor performance of loans and higher standardization (a new officer tends to over-rely on hard information). This is untrue for two reasons. Firstly, such an effect should also be present, and perhaps to a higher degree, when officers are rotated without the change in organizational design. We exploit an internal rotation policy of branch managers and do not find this to be the case (see Table (17)). Secondly, we do not find the effect to be transient, that is, the effects do not reverse after the officer gets comfortable in the new system. The results on dynamics confirm this.

8.2 Manipulation

As noted above, the reorganization of a branch entails a change in the loan approval limit. This change in the cut-off point may alter the composition of borrowers around the threshold. This can be demonstrated by the following situation. An individual with no credit history or adverse credit history requests a loan for 550,000 rupees from a manager whose approval limit is only 500,000 rupees. Even though, after a thorough investigation the manager knows that the borrower is of the good-type, the very nature of soft information makes it extremely difficult to transmit it to the regional office. Hence, forwarding the application further would clearly lead to a rejection. Anticipating this, the manager may instead offer the client a loan of 500,000 rupees that falls within his approval limit. If such terms are acceptable to both parties, a loan is granted. However, in the period after upgradation, the branch manager that is heading this branch does not face this dilemma (if the approval limit is above 550,000 rupees) as he can approve this loan within the branch. He would then simply approve the 550,000 rupee loan. Thus manipulation of the loan amount may change the composition of borrowers around the threshold.

Additional tests show that this does not affect our results. We begin by plotting the Epanechnikov kernel density functions around the normalized cut-off for pre- and post-treatment periods. As can be seen in Figure (11), both distributions are statistically the same around the cut-off point and the Kolmogorov-Smirnov test for the equality of the distributions cannot be rejected at the 1 percent level. In other words, we find no evidence of any bunching around the threshold.[15] We next disregard loans that are within 20 percent window around the cut-off[16] and re-estimate our specification. Our results remain virtually the same with the lower approval limit (Table

[15] The humps in the distribution represent round numbers that are popular loan amounts such as 450,000 and 550,000.

[16] For example, if the cut-off is 500,000 rupees then all loans from 400,000 to 500,000 would not be considered.

(18)). Finally, as already noted, the smallest common cut-off is binding only for a subset of bank branches (roughly a sixth of branches). Excluding those branches leaves our results qualitatively unchanged. In sum, all three tests allay all concerns of manipulation around the cut-off.

9 Conclusion

A large literature in financial intermediation delegates the role of screening and monitoring to banks. According to these theories, screening and monitoring by banks is efficient since it reduces duplication in monitoring costs, and free-riding problems that are associated with multiple creditors. But for a bank to deliver on its promise, it must have the correct organizational design in place, just like any other firm.

While there are many theories on the organizational structure of a firm and the associated trade-offs, there has been far less empirical work. In this paper, we use a quasi-natural experiment research design to provide a causal link between organizational design and production of soft information. Overall, our findings suggest that a centralized organizational structure distorts production and communication of soft information and leads to standardization of loan contracts. Furthermore, our study also suggests that adding one more managerial layer increases the delinquency rate by 30 percent and decreases the return on loan by 14 percent. Most importantly, we are able to provide a direct evidence on managerial intervention and identify the incentive-based theories of organizational hierarchy by Aghion and Tirole (1997) and Stein (2002).

Our paper also shows that large organizations mitigate the problem of transmitting soft information by creating within-firm sub-organizations. Although in line with Stein's (2002) view that more hierarchical firms tend to base their decisions on hard information, this result shows that even if a firm appears to be hierarchical from outside, it can organize itself internally in a way that reduces this problem.

It is important to note that while this paper identifies the effect of hierarchy on information production and the channel through which this happens, it does so in a setting where incentive contracts are fixed across different branches. While this is ideal from an identification point of view, it leaves the following question unanswered: Can contractual flexibility remove the underproduction of information in hierarchical branches, or are there limits to delegation in these branches? This is an important question for future research.

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Figure 1: Geographical Distribution of Branches, Weighted by Total Lending

The center indicates the location of the branch by postal code. The size corresponds to the total amount lent in the branch in 2006.

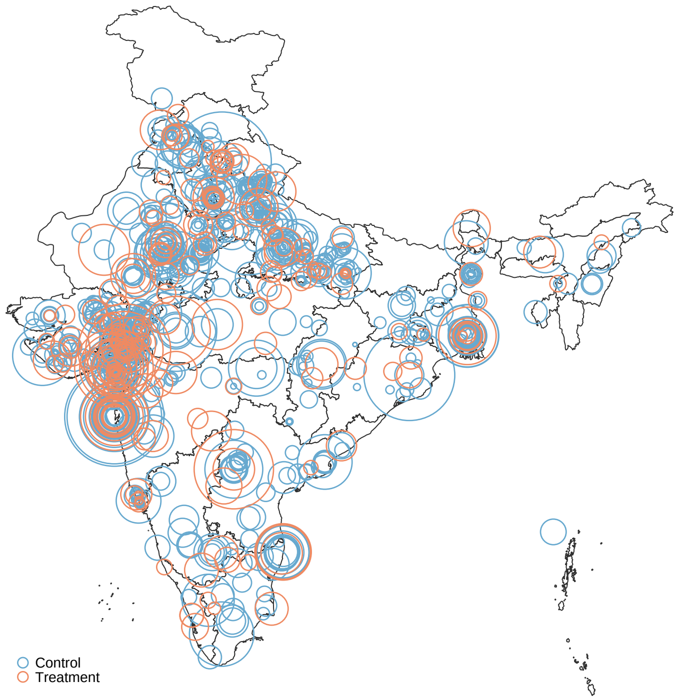

Figure 2: Organizational Design

The bank's organizational design consists of ten layers described below. A higher-ranking manager has more decisional power and authority. The top five layers, marked with an asterisk, are the senior management team, mainly involved in business development. The lower three focus on the operational side of lending.

Position	Level of a Manager
Chairman and Managing Director	*8**
Executive Director	*7**
General Manager	*6**
Deputy General Manager	*5**
Assistant General Manager	*4**
Chief Manager	3
Senior Manager	2
Junior Manager	1

Figure 3: Internal Organizational Design

Below is a schematic illustration of the bank and its branches. Each level has a specified approval limit on the size of the loan. If the loan falls outside of the branch manager's limits, it is sent either to the regional, zone, or head office for approval, depending on the size of the loan.

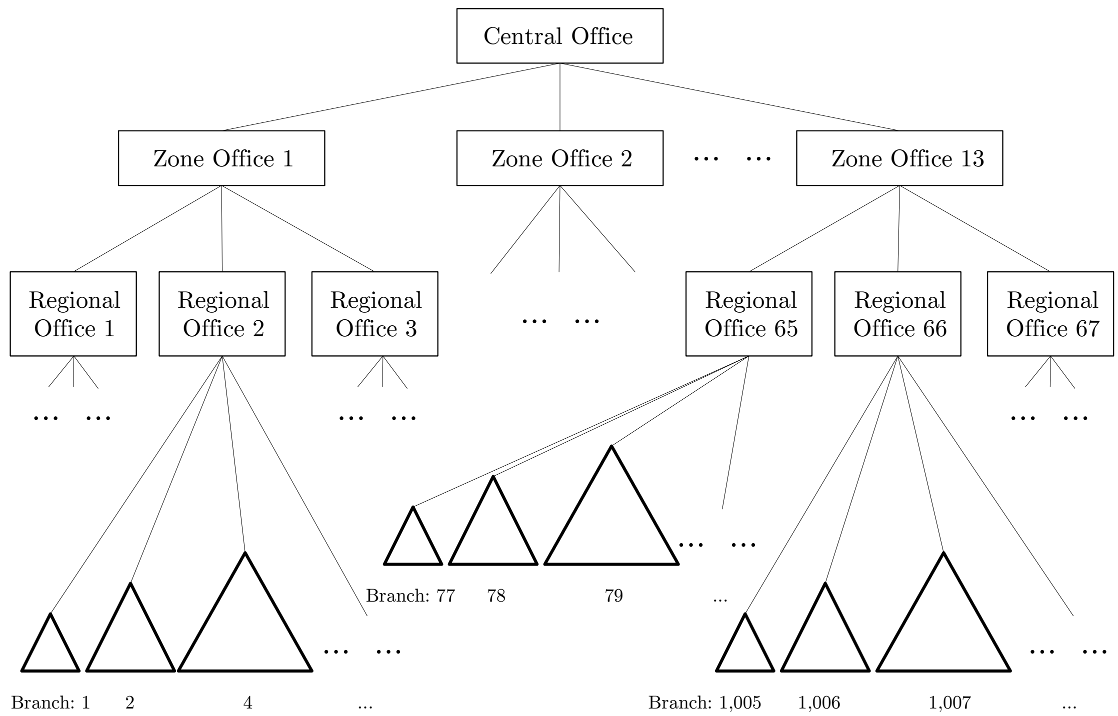

Figure 4: Branch Office Design

Below is a schematic illustration of the bank's branches. Each level has a specified approval limit on the size of the loan. If the loan falls outside of the branch manager's limits, it is sent either to the regional, zone, or head office for approval, depending on the size of the loan. Our sample consists of three organizational designs: decentralized (Level 1), medium hierarchy (Level 2), and centralized (Level 3). The more hierarchical the branch, the higher the approval limits of its manager. Our analysis focuses on all new individual loans eligible for approval at any organizational design, i.e., the loans that fall below the limit of the least hierarchical branch (the triangles at the bottom of the chart).

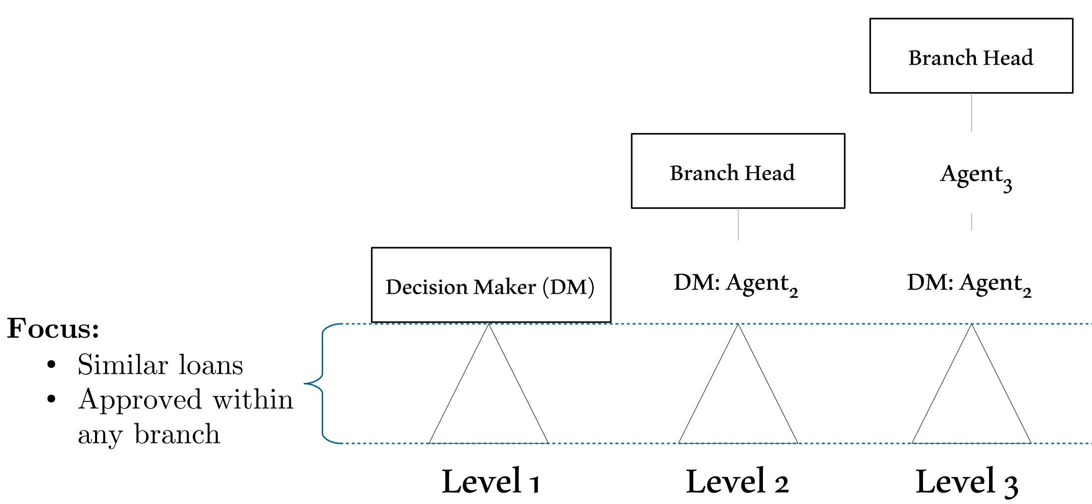

Figure 5: Loan Approval Process

The flowchart below describes the loan approval process. It starts with a loan application at the branch office and continues until the loan is approved or rejected either at the branch or other external office.

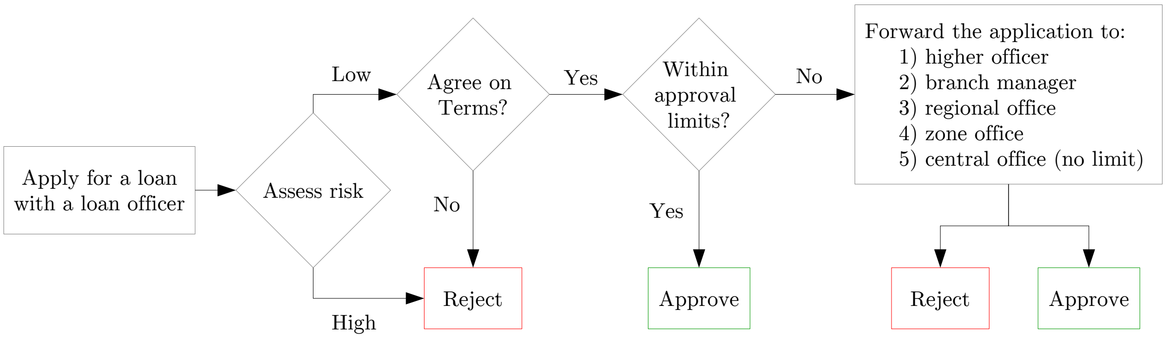

Figure 6: Identification Strategy

The figure below describes our differences-in-differences (DID) identification strategy. We estimate the effect of organizational design on a set of loans eligible for approval both before and after the treatment (treatment group). Then we compare our estimated effect with the results of similar branches whose organizational design was left unchanged (control group).

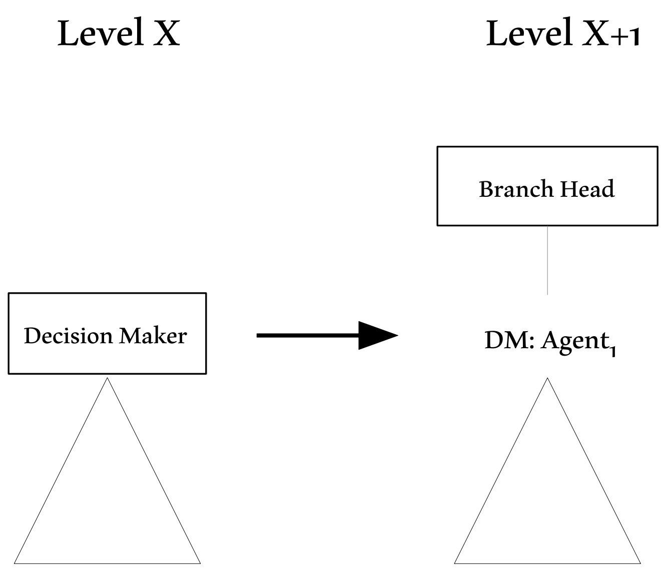

Figure 7: Changes in Branch Levels

Below we plot the distribution of branch level changes over time. In total 500 branches (or roughly 20% of total) were reorganized.

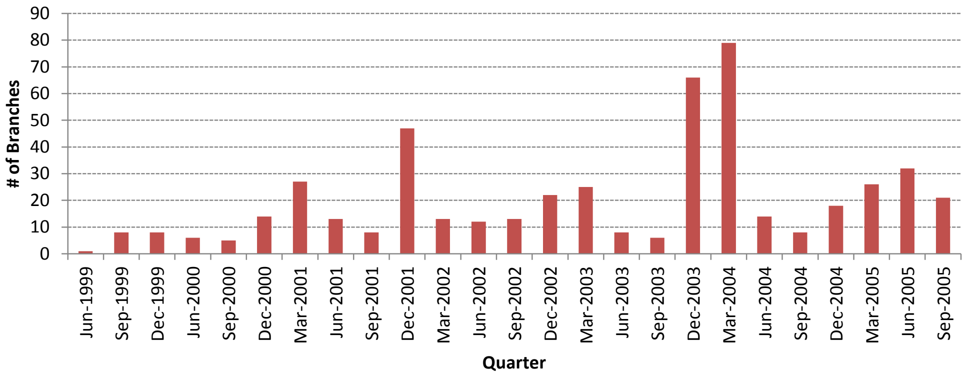

Figure 8: Transition Probabilities

The graphs below plot the transition probabilities (rupee-weighted) of loans that subsequently defaulted (i.e., the legal proceedings with the borrower are finalized). The plot on the left presents the default probabilities for loans that are 60 or more days late, whereas the one on the right presents those for loans that are paid on time or are less than 60 days late. We track loans from the quarter they become 60+ days late and plot the average loans that default conditional on their age at the quarter becoming delinquent (Figure (a)). Similarly, we track loans from their origination quarter and plot the average loans that default conditional on the age of a loan (Figure (b)). Both graphs are smoothed using fractional-polynomial approximation.

(a) 60+ Delinquent to Default

(b) Healthy to Default

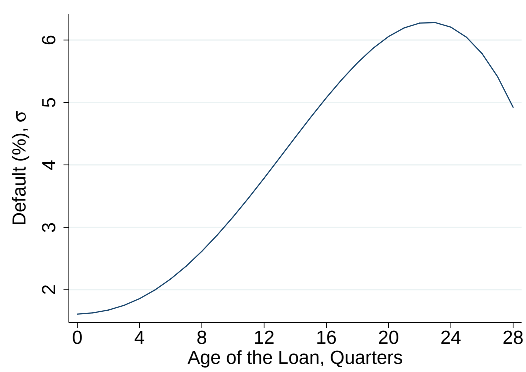

Figure 9: Cross-Sectional Variation

The graph below plots the kernel density functions of standardized residuals (estimated by equation (5)) for loans falling within the approval limits of all branches. The graph is trimmed to show 98% of the sample.

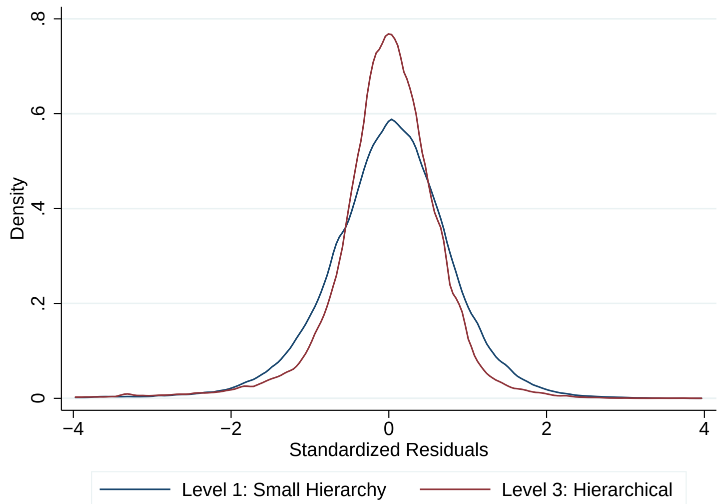

Figure 10: Dynamics Plot: Soft Information

The horizontal axis shows the time, in quarters, since the branch reorganization (0 represents the first two quarters of the reorganization). The vertical axis measures the soft information measured as the standard deviation of the residual estimated using equation (5). The coefficients are estimated using equation (3). The dashed lines indicate the 95% confidence interval.

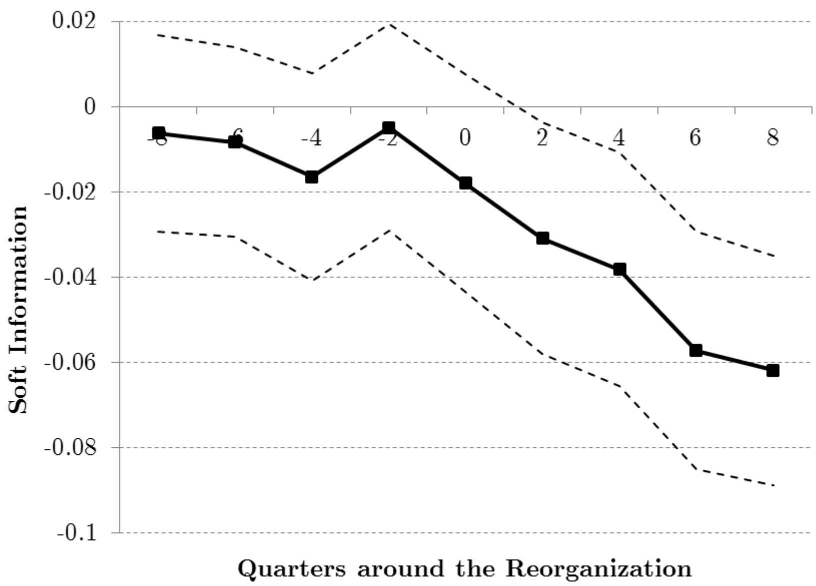

Figure 11: Distribution Around the Approval Threshold

The graph below plots kernel density functions of loans around the threshold value for pre- and post-treatment periods. The threshold is normalized to equal 1. We show the frequency of all loans that fall within the 40% window around the threshold value. The values to the right of 1.00 are above the threshold, while the values to the left are below it.

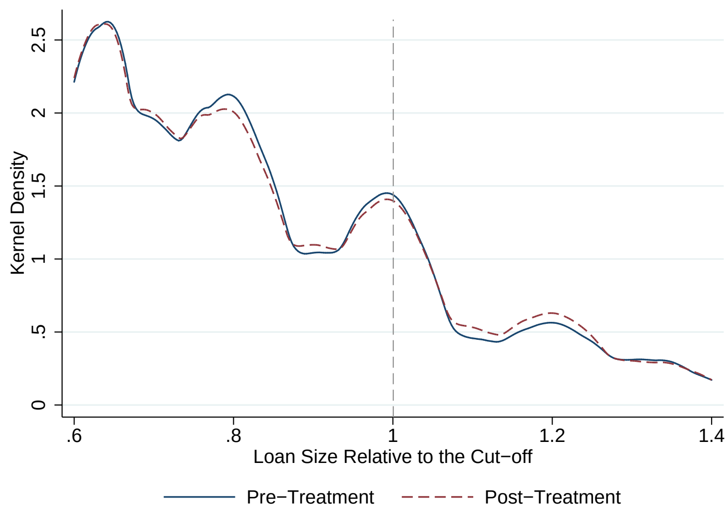

Table 1: Summary Statistics

This table reports branch-quarter summary statistics of new individual loans. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. We report the mean, standard deviation, the 1st percentile, median, and the 99th percentile for all the variables.

	Mean	Std. Dev.	p1	p50	p99
	Branch-Quarter Statistics (N=54,079)				
New Credit (1,000s of rupees)	1,175.1	2,063.4	31.0	726.4	6,650.1
Mean Loan Amount (1,000s of rupees)	56.0	43.5	7.8	42.8	216.5
# of Borrowers	24.5	39.1	2.0	15.0	143.0
Fraction of Borrowers delinquent within a year	0.050	0.111	0.000	0.000	0.500
Fraction of Debt delinquent within a year	0.042	0.111	0.000	0.000	0.570
Return on Loans (value-weighted)	0.070	0.079	-0.244	0.083	0.150
Interest Rate	11.44	1.83	8.19	11.60	15.84
Maturity (years)	4.15	2.26	0.60	4.00	11.11
Collateral-to-Loan (median)	6.75	406.98	0.00	1.42	19.12
Std. Dev. Debt (1,000s of rupees)	57.6	44.7	2.3	47.9	184.1
IQR Debt (1,000s of rupees)	54.6	66.8	0.7	28.2	309.8
Branch Level	1.4	0.6	1	1	3
Branch Level (treated)	1.7	0.7	1	2	3

Table 2: Summary Statistics: Cross-Section

This table reports branch-quarter summary statistics of new individual loans across organizational designs. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. We report the mean and the standard deviation for all the variables.

	Mean Loan Amount		# of Borrowers		Fraction of Debt del. within a year		Return on Loans	
Branch Level (# Obs)	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Level 1 (34,068)	46,303	35,698	24.65	30.48	0.046	0.116	0.066	0.083
Level 2 (17,139)	70,231	48,438	25.27	52.53	0.039	0.105	0.074	0.073
Level 3 (2,872)	85,918	57,944	17.94	35.20	0.024	0.083	0.078	0.067

Table 3: Credit Rationing, Number of Borrowers and Total Lending

This table reports the effect of organizational design on total new lending to small individual borrowers (columns 1, 4, and 7), the number of new individual borrowers (columns 2, 5, and 8), and loan size (columns 3, 6, and 9), using specification (1). The unit of analysis is branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	ln (New Ind. $\text{Debt}_{b,q}$)	ln (# of $\text{brwrs}_{b,q}$)	ln $\left(\overline{\text{Loan}}_{b,q}\right)$	ln (New Ind. $\text{Debt}_{b,q}$)	ln (# of $\text{brwrs}_{b,q}$)	ln $\left(\overline{\text{Loan}}_{b,q}\right)$	ln (New Ind. $\text{Debt}_{b,q}$)	ln (# of $\text{brwrs}_{b,q}$)	ln $\left(\overline{\text{Loan}}_{b,q}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Branch Level	-0.099***	-0.045*	-0.054***	-0.083**	-0.031	-0.052***			
	(0.030)	(0.025)	(0.017)	(0.033)	(0.026)	(0.018)			
Before^{-2}							0.032	0.039	-0.006
							(0.040)	(0.032)	(0.024)
Before^{0}							-0.037	0.014	-0.051**
							(0.041)	(0.033)	(0.024)
After^{2}							-0.123***	-0.055	-0.068***
							(0.043)	(0.034)	(0.026)
After^{4+}							-0.123***	-0.058*	-0.065***
							(0.039)	(0.033)	(0.022)
Observations	54,079	54,079	54,079	54,079	54,079	54,079	54,079	54,079	54,079
Adj-R^2	0.396	0.450	0.403	0.464	0.539	0.444	0.396	0.450	0.403
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N	N	N	Y	Y	Y
Quarter-District FE	N	N	N	Y	Y	Y	N	N	N

Table 4: Effect of Organizational Design on Loan Repayment

This table reports the effect of organizational structure on loan repayment (columns 1, 2, and 3) and its dynamics (columns 4 and 5), using specification (1). Column 3 reports the effect on value-weighted default rates after controlling for local demand shocks through quarter-district fixed effects instead of quarterly fixed effects. Column 4 reports the difference between the estimated coefficients on equally- and value-weighted default rates. Defaults are measured as a fraction of loans that are over 60 days late one year forward, estimated at the branch-quarter level. The sample considers individual, new loans that can be approved within any branch. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The standard errors are reported in parentheses and clustered at the branch level. P-values are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

	Defaults (60+ days late)					
	Equally Weighted	Value Weighted	Value Weighted	Difference (2)-(1)	Equally Weighted	Value Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Branch Level	0.010***	0.014***	0.009***	0.004***		
	(0.003)	(0.003)	(0.003)	[0.008]		
Before^{-2}					0.003	0.001
					(0.004)	(0.004)
Before^{0}					0.010***	0.013***
					(0.004)	(0.004)
After^{2}					0.009**	0.013***
					(0.004)	(0.003)
After^{4+}					0.012***	0.015***
					(0.004)	(0.003)
Observations	54,079	54,079	54,079		54,079	54,079
Adj-R^2	0.234	0.183	0.271		0.234	0.183
Branch FE	Y	Y	Y		Y	Y
Quarter FE	Y	Y	N		Y	Y
Quarter-District FE	N	N	Y		N	N

Table 5: Recovery Rates

The table below reports the mean (1) and the standard error (2) of our estimated recovery rates which are used in return on loan calculations. Additionally, column (3) reports the number of observations used in calculating the rates. We report rupee-weighted recovery rates from the defaulted loans computed as the value recovered against the defaulted principal and interest due for both secured and unsecured loans. Due to data limitations, the recovery rates are calculated only for loans written off in the first quarter of 2006. Unfortunately, we do not have the data from other quarters.

		Mean	S.E.	Obs.
		(1)	(2)	(3)
Recovery rate (δ)	Branch Hierarchy:			
Secured	Decentralized	48.07	0.56	2,516
	Medium	39.76	0.70	2,240
	Centralized	40.77	1.69	358
Unsecured	Decentralized	30.07	0.46	4,420
	Medium	23.47	0.46	3,699
	Centralized	23.28	1.02	595

Table 6: Return on Loans

This table reports the effect of organizational structure on the equally- and value-weighted return on loans (columns 1, 2, and 3) and its dynamics (columns 4 and 5) using specification (1). Column 3 reports the effect on value-weighted returns after controlling for local demand shocks through quarter-district fixed effects instead of quarterly fixed effects. Column 4 reports the difference between the estimated coefficients on equally and value-weighted returns. The unit of analysis is branch-quarter return on loans. First, we estimate the return for each loan, as defined in equation (2). Then we aggregate the loan-level estimate at the branch-quarter level using equal or value weights. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. Standard errors in parentheses are corrected for clustering at the branch level. P-values are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

	ROL					
	Equally Weighted	Value Weighted	Value Weighted	Difference (2)-(1)	Equally Weighted	Value Weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Branch Level	-0.007***	-0.010***	-0.006***	-0.003**		
	(0.002)	(0.002)	(0.002)	(0.011)		
Before^{-2}					-0.001	-0.000
					(0.003)	(0.003)
Before^{0}					-0.007**	-0.010***
					(0.003)	(0.003)
After^{2}					-0.003	-0.010***
					(0.003)	(0.002)
After^{4+}					-0.008***	-0.012***
					(0.003)	(0.002)
Observations	54,079	54,079	54,079		54,079	54,079
Adj-R^2	0.155	0.136	0.207		0.155	0.136
Branch FE	Y	Y	Y		Y	Y
Quarter FE	Y	Y	N		Y	Y
Quarter-District FE	N	N	Y		N	N

Table 7: Measures of Soft Information

The table below reports the effect of organizational design on soft information: inter-quartile range of debt (columns 1, 3, and 5) and standard deviation of debt (columns 2, 4, and 6), estimated in equation (5). Columns 3 and 4 report the effect on soft information after controlling for local demand shocks through quarter-district fixed effects instead of quarterly fixed effects. The unit of analysis is branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable:	$\ln\left(\text{IQR}_{b,q}\right)$	$\ln\left(\sigma\text{Loan}_{b,q}\right)$	$\ln\left(\text{IQR}_{b,q}\right)$	$\ln\left(\sigma\text{Loan}_{b,q}\right)$	$\ln\left(\text{IQR}_{b,q}\right)$	$\ln\left(\sigma\text{Loan}_{b,q}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)
Branch Level	-0.123***	-0.095***	-0.112***	-0.076***		
	(0.026)	(0.021)	(0.029)	(0.023)		
Before^{-2}					-0.026	0.020
					(0.040)	(0.032)
Before^{0}					-0.135***	-0.050
					(0.042)	(0.034)
After^{2}					-0.111***	-0.102***
					(0.039)	(0.035)
After^{4+}					-0.145***	-0.117***
					(0.034)	(0.027)
Observations	54,079	54,079	54,079	54,079	54,079	54,079
Adj-R^2	0.271	0.291	0.298	0.321	0.271	0.291
Branch FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	N	N	Y	Y
Quarter-District FE	N	N	Y	Y	N	N

Table 8: First Stage Results

The table below reports the coefficients obtained from the first stage regression, used to estimate loan-level soft information (see Equation (5)). The dependent variable is the natural logarithm of the outstanding loan balance. The specification controls for the priority sector, the loan type, the collateral type, the branch, and quarterly fixed effects. To account for the potential differences in the realization value at seizure across collateral types, we estimate the interacted collateral type and nominal value coefficients. We report the average coefficient on the collateral value and provide a joint F-test that all coefficients are jointly equal to zero. The standard errors are reported in parentheses (except for the collateral value) and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable:	ln (Loan Size)
Maturity	0.0365***
	(0.0038)
Female	-0.1009***
	(0.0053)
ln (1+Value) x Collateral Type	0.1571***
F-test (p-val)	0.0000
Priority Sector	-0.0081
	(0.0105)
Observations	1,742,092
Adjusted R^2	0.55
Other Controls	Y
Branch FE	Y
Quarter FE	Y

Table 9: Effects of Organizational Structure on Loan Standardization

In this table, we report the effect of organizational hierarchy on the production of soft information using specification (1). The dependent variable $\hat{\sigma}\left(\epsilon_{b,t}\right)$ captures the intensity of soft information at branch b, in quarter q. It is estimated as the standard deviation of the residuals obtained from the regression model defined in Equation (5). The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. The columns (1) - (4) report cross-sectional results. Column (5) reports the within-branch results. Column (6) reports the results after controlling for local demand shocks through quarter-district fixed effects instead of quarterly fixed effects. The coefficients in column (7) report the cumulative dynamics of the organizational change. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} was a dummy variable that equals one (minus one) if the branch is upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four or more quarters ago. For cross-sectional comparison, the measure is normalized by the standard deviation of the dependent variable (log outstanding amount) at the branch level. The sample is trimmed for the upper 1st percentile of the soft information. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	Dependent Variable: Soft Information $\hat{\sigma}\left(\epsilon_{b,t}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Branch Level	-0.048***	-0.042***	-0.038***	-0.043***	-0.033***	-0.022**	
	(0.003)	(0.004)	(0.004)	(0.006)	(0.008)	(0.009)	
Before^{-2}							-0.000
							(0.011)
Before^{0}							-0.011
							(0.011)
After^{2}							-0.022*
							(0.012)
After^{4+}							-0.046***
							(0.010)
Observations	54,079	54,079	54,079	54,079	54,079	54,079	54,079
Adj-R^2	0.02	0.03	0.04	0.04	0.110	0.138	0.110
Initial Level FE	N	N	N	Y	N	N	N
Zone FE	N	Y	N	N	N	N	N
Region FE	N	N	Y	Y	N	N	N
Branch FE	N	N	N	N	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	N	Y
Quarter-District FE	N	N	N	N	N	Y	N

Table 10: Default Predictability

In this table, we report the predictive power of hard information on future performance of loans, depending on the organizational hierarchy. We estimate the R-square of hard information for each district-quarter-hierarchy level, using specification defined in equation (6). Then using the estimated R-square at a district-quarter-hierarchy level we run the following second stage regression

$$\widehat{\text{R-squared}}_{dqh} = \tau_{dq} + \text{Branch Level}_{dqh} + \epsilon_{dqh}$$

where d stands for district, q for quarter and h for branch hierarchy level. We report the results for three first-stage specifications. In Model 1 we control for the natural logarithm of loan size, interest rate, loan-to-value ration and maturity. In Model 2, in addition to the variables in Model 1, we also control for gender and priority sector. In Model 3, in addition to the variables in Models 1 and 2, we also control for product group fixed effects. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. The standard errors are reported in parentheses and clustered at the district level. * significant at 10%; ** significant at 5%; *** significant at 1%.

	Model 1	Model 2	Model 3
Branch Level	0.079***	0.097***	0.108***
	(0.000)	(0.000)	(0.003)
Adj R2	7,260	6,170	4,205
Obs	0.271	0.298	0.249
District-Quarter FE	Y	Y	Y

Table 11: Effect of Organizational Design on Large Loans, Eligible for Approval Internally

This table reports the effect of organizational design on loans that had to be approved externally (e.g., regional office) before the change, but can be approved internally since the increase in the approval limit of the branch. We report the estimated effect on log debt amount (columns 1 and 4), the probability of receiving any credit (columns 2 and 5), and soft information (columns 3 and 6) using specification (1). The measure of soft information is the mean absolute value of the residual, estimated by Equation (5). The unit of analysis is branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The standard errors are reported in the parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	$\ln(1+\text{Value}_{b,q})$	$\mathbb{1}_{\#\text{Loans}_{b,q}>0}$	Soft Info	$\ln(1+\text{Value}_{b,q})$	$\mathbb{1}_{\#\text{Loans}_{b,q}>0}$	Soft Info
	(1)	(2)	(3)	(4)	(5)	(6)
Branch Level	0.509***	0.033***	0.016***			
	(0.150)	(0.011)	(0.004)			
Before^{-2}				0.305	0.019	0.005
				(0.205)	(0.015)	(0.005)
Before^{0}				0.617***	0.041***	0.013**
				(0.210)	(0.015)	(0.006)
After^{2}				0.530**	0.034**	0.013**
				(0.221)	(0.016)	(0.005)
After^{4+}				0.565***	0.036**	0.019***
				(0.202)	(0.014)	(0.005)
Observations	54,079	54,079	54,079	54,079	54,079	54,079
$\text{Adj} - R^2$	0.324	0.309	0.253	0.324	0.309	0.253
Quarter FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y

Table 12: Combined Retail Portfolio

In this table, we report the effect of the organizational hierarchy for the combined retail portfolio (i.e. it includes both small and large loans). We report the effect on the soft information, standard deviation of debt, inter-quartile range of debt, value-weighted defaults and return on loans, and total new lending to retail borrowers in columns 1 through 6, respectively. The unit of analysis is a branch-quarter. The measure of soft information is estimated as the standard deviation of the residuals obtained from the regression model defined in Equation (5). The defaults are measured as whether a loan is over 60 days late one year forward. The return on loans is measured as defined in equation (2). The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	Soft info	$\ln\left(\sigma_{\text{Loan}_{b,q}}\right)$	$\ln\left(\text{IQR}_{b,q}\right)$	VW Default	VW ROL	$\ln\left(\text{New Ind. Debt}_{b,q}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)
Branch Level	-0.033***	-0.043*	-0.092***	0.013***	-0.004**	-0.038
	(0.008)	(0.023)	(0.027)	(0.003)	(0.002)	(0.030)
Obs	54,079	54,079	54,067	54,079	54,079	54,079
Adj-R^2	0.107	0.408	0.350	0.187	0.157	0.469
Branch FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y

Table 13: Organizational Hierarchy and Corruption

The table reports the effect of organizational design depending on the severity of corruption in the area. We report the estimated effect on the measure of soft information (column 1), value-weighted return on loans (column 2) and default (column 3). The unit of analysis is branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. *BIMARU* is a dummy variable equal to one if the branch is located in states of Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh, which have been singled out for corruption and dysfunction. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	Soft Info	VW ROL	VW Default
	(1)	(2)	(3)
Branch Level	-0.046***	-0.016***	0.020***
	(0.000)	(0.000)	(0.000)
Branch Level x BIMARU	0.043**	0.019***	-0.021***
	(0.017)	(0.000)	(0.000)
Obs	53,579	53,579	53,579
Adj-R^2	0.110	0.136	0.183
Branch FE	Y	Y	Y
Quarter FE	Y	Y	Y

Table 14: Bank Competition

This table reports the effect of organizational design depending on the bank competition in the area. We report the estimated effect on the three measures of soft information (columns 1 to 3), value-weighted return on loans (column 4) and default (column 5), log debt amount (columns 6), and the number of borrowers (column 7). The unit of analysis is branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Branch Density is the log of number of bank branches scaled by the size of population (in 1,000) in a district in 2001. The variable is winsorized for a single outlier district that corresponds to 3% of the sample. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	Soft info	$\ln(\mathrm{IQR}_{b,q})$	$\ln\left(\sigma_{\mathrm{Loan}_{b,q}}\right)$	VW ROL	VW Defaults	ln (New Ind. $\mathrm{Debt}_{b,q}$)	ln (# of $\mathrm{brwrs}_{b,q}$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Branch Level	-0.116***	-0.192***	-0.203***	-0.006***	0.024***	-0.323***	-0.295***
	(0.021)	(0.073)	(0.058)	(0.001)	(0.006)	(0.095)	(0.073)
Branch Level x Branch Density	-0.030***	-0.025	-0.037*	-0.001***	0.004*	-0.080***	-0.090***
	(0.007)	(0.024)	(0.019)	(0.000)	(0.002)	(0.031)	(0.024)
Observations	54,079	54,079	54,079	54,079	54,079	54,079	54,079
$\mathrm{Adj}-R^2$	0.108	0.271	0.292	0.133	0.177	0.390	0.444
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y

Table 15: Organizational Hierarchy and Interference

This table reports two results. First, the effect of organizational design on the fraction of loans that have been approved by the manager with the smallest approval limit – the junior manager (column 1 in Panel A). Second, the cross-sectional treatment effect depending on the degree of delegation within the branch (Panel B). In Panel B we report the estimated effect on the measure of soft information (column 2), value-weighted return on loans (column 3) and default (column 4). The unit of analysis is a branch-quarter. The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. The variable $\overline{\textit{\%, Junior Mgr}}$ is the average fraction of loans that have been delegated to the junior manager at the branch level. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	% Approved by Junior Manager
	(1)
Panel A: Delegation	
Branch Level	-0.054***
	(0.010)
Adj R2	54,079
Obs	0.36
Quarter FE	Y
Branch FE	Y

	Soft Info	VW ROL	Defaults
	(2)	(3)	(4)
Panel B: Cross-sectional effects by degree of delegation			
Branch Level	-0.156***	-0.026***	0.033***
	(0.027)	(0.007)	(0.007)
Branch Level x $\overline{\textit{\%, Junior Mgr}}$	0.145***	0.019**	-0.023***
	(0.031)	(0.008)	(0.009)
Observations	54,079	54,079	54,079
$\mathrm{Adj}-R^2$	0.110	0.136	0.183
Quarter FE	Y	Y	Y
Branch FE	Y	Y	Y

Table 16: Managerial Style and Performance of a Branch

In this table, we report the effect of the managerial style. We report the effect on the soft information, standard deviation of debt, inter-quartile range of debt, value-weighted defaults and return on loans, and total new lending to retail borrowers in columns 1 through 6, respectively. The unit of analysis is a branch-quarter. The measure of soft information is estimated as the standard deviation of the residuals obtained from the regression model defined in Equation (5). The defaults are measured as whether a loan is over 60 days late one year forward. The return on loans is measured as defined in equation (2). The *Managerial Style* is estimated using equation (7), where the higher the value of the variable, the more likely is the manager to delegate a loan application. The specification exploits manager rotation. The standard errors are reported in parentheses and clustered at the manager level. P-values are reported in square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

	Soft Info	$\ln\left(\sigma_{\text{Loan}_{b,q}}\right)$	$\ln\left(\text{IQR}_{b,q}\right)$	VW Default	VW ROL	$\ln\left(\text{New Ind. Debt}_{b,q}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)
Managerial Style	0.076***	0.443***	0.180*	-0.017*	0.018**	0.869***
	(0.029)	(0.102)	(0.105)	(0.010)	(0.007)	(0.124)
Adj R2	0.13	0.33	0.31	0.18	0.15	0.44
Obs	35,580	35,580	35,580	35,580	35,580	35,580
Quarter-FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y

Table 17: Manager Rotation

The table reports the results of manager rotation when the organizational design remains unchanged. We show the estimated effects on the soft information (column 1), the value weighted return on loans (column 2) and defaults (column 3), log average loan (column 4), log total new individual lending (column 5), standard deviation of debt (column 6), and the inter-quartile range of debt (column 7). The unit of analysis is a branch-quarter. The variable *Change* is a dummy variable equal to one if the manager changed at the branch b, in quarter q, and zero otherwise. The measure of soft information is estimated as the standard deviation of the residuals obtained from the regression model defined in Equation (5). The defaults are measured as whether a loan is over 60 days late one year forward. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	Soft Info	VW ROL	VW Default	$\ln\left(\overline{\text{Loan}}_{b,q}\right)$	$\ln\left(\text{New Ind. Debt}_{b,q}\right)$	$\ln\left(\sigma_{\text{Loan}_{b,q}}\right)$	$\ln\left(\text{IQR}_{b,q}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change	-0.012	-0.002	-0.001	0.014	-0.012	0.029	0.038
	(0.011)	(0.003)	(0.004)	(0.023)	(0.041)	(0.031)	(0.038)
Obs	33,684	33,684	33,684	33,684	33,684	33,684	33,684
Adj-R^2	0.135	0.131	0.188	0.454	0.395	0.328	0.297
Branch FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y

Table 18: Loan Size Manipulation Around the Approval Limit

In this table, we report the effect of the organizational hierarchy for the loans well below the loan approval limit of the head of the branch. We redefine the approval limit as 80% of the true threshold. We report the effect on the value-weighted defaults (column 1) and return on loans (column 2), and the soft information (columns 3 and 4). The unit of analysis is a branch-quarter. The measure of soft information is estimated as the standard deviation of the residuals obtained from the regression model defined in Equation (5). The defaults are measured as whether a loan is over 60 days late one year forward. The return on loans is measured as defined in equation (2). The variable *Branch Level* is a number between one and three, where the lowest value (1) and the highest value (3) characterize the least hierarchical branches and the most hierarchical branches, respectively. Before^{-2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) in one or two quarters. Before^{0} is a dummy variable that equals one (minus one) if the branch was upgraded this quarter or one quarter ago. After^{2} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. After^{4+} is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The standard errors are reported in parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

	VW Def	VW ROL	Soft Info	
	(1)	(2)	(3)	(4)
Branch Level	0.013***	-0.008***	-0.035***	
	(0.003)	(0.004)	(0.008)	
Before^{-2}				0.006
				(0.011)
Before^{0}				-0.009
				(0.012)
After^{2}				-0.022*
				(0.013)
After^{4+}				-0.047***
				(0.010)
Observations	54,079	54,079	54,079	54,079
Adj-R^2	0.18	0.13	0.11	0.11
Branch FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y

A Example Loan Term Sheet

Table A1: Interest Rates and Loans

The table provides three examples of loan terms by product type. The term sheet defines the relationship betweem the loan size, the maturity, and the interest rate. The terms are set centrally by the head office and are uniform for all bank branches. Please note that the numbers have been changed to preserve the bank's identity.

Home Loan		
Maturity	$\leq 2,000,000$	$> 2,000,000$
Up to 5 years	1.5% + base rate	3.0% + base rate
Over 5 years & up to 20 years	2.0% + base rate	4.0% + base rate
Home Improvement Loan		
	All sizes	
All maturities	3.0% + base rate	
Car Loan		
	All sizes	
Up to 5 years	3.0% + base rate	
Over 5 years	4.0% + base rate	

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