# How Organizational Hierarchy Affects Information Production

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**Abstract**

This paper empirically investigates how organizational hierarchy affects the allocation of credit inside 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-difference research strategy, we find that an increase in hierarchy of a branch decreases its ability to produce "soft" information on loans. Specifically, we find that an increase in hierarchy leads to more standardization of loans and rationing of "soft information" loans. Furthermore, this standardization leads to a reduction in performance on loans – delinquency rates and returns on similar loans are lower in more hierarchical branches.

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

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# 1 Introduction

Over the recent years there has been a substantial change in the landscape of lending with banks getting larger, globalized and more complex (Mester, 2012; Herring and Carmassi, 2012). While it is understood that banks benefit firm 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 change 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 organizational structure of banks may perpetuate inequality in the society. In this paper we examine how organizational hierarchy affects the allocation of credit.

There is now a growing recognition that organizational design matters. But 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 organizational design of firms, but also requires a comprehensive information on outcome variables to identify the effect of changes in organizational design. This is a tough ask, as such datasets are difficult to come by. 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 with concerns over the nature of the omitted variables. To make any causal claims, the researcher has to seek for some exogenous perturbation 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 has 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 organizational design variables of branches, which allow us to utilize the within-branch variation for identification. The identification strategy exploits changes in organizational design, brought about by a bank-level pre-determined reorganizational rule, discussed in details later, and employs a difference-in-difference (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 find 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 informationally sensitive 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 lower by 30 percent and a similar loan portfolio in the decentralized branch generates a 15 percent higher returns for the bank. Interestingly, the effects are stronger when we examine value-weighted, instead of equally-weighted, defaults and returns, suggesting that the result come from a better allocation of credit in decentralized structures. We show that none of the results are driven by pre-treatment trends.

We next investigate the mechanism that delivers these results. Clearly, our result are consistent with better information being produced on loans in more decentralized structures and provide support for the incentive based theories on organizational design (Stein, 2002; Aghion and Tirole, 1997). To sharpen our results further, we examine the contract terms on loan agreements. Specifically, we examine the second moment of contract terms, similar in spirit to the Rajan et al. (2013) test. Specifically, Rajan et al. (2013) argue that more information should increase the variance of the contract terms for the same set of borrowers – more information, produced in decentralized structures, allows banks to discriminate amongst borrowers. To the extent that the borrowers are not aware of the changes in the internal organization of the bank, a reasonable assumption in our setting, an increase in variance on contractual terms indicates more information being collected on loans. Consistent with this prediction, we find that decentralized structures produce more information on loans. Specifically, we find that a new layer in the hierarchy reduces the variance of contract terms and increases the loan contract standardization by 5.3 percent.

An interesting feature of our setting is that larger and more hierarchical structures are also headed by more senior officers, who can approve even higher loan amounts. To make reasonable comparisons, we investigate the portfolio of retail loans that are eligible across all structures, that is, the lowest common denominator. If a loan request for an amount that is above the cut-off limit of a given branch comes to the branch, it is automatically sent to a higher level office at the regional level. So an increase in organizational level implies that certain loans that would have otherwise been sent to a more senior branch are now approved within the branch. On examining the subset of loans that were sent to the regional office before the organizational change, but were approved in the branch after the change, we find both that the branch issues more such loans and that it generates more soft information on them. Given that these loans witnessed 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.

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 strong in more competitive banking markets. 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[1] the adverse selection is less severe.

The cross-sectional test with competition also allows us to disentangle supply side- from demand-side effects. Specifically, it is argued that more hierarchical structures reduce a bank's ability to produce information on loans. This would change the allocation of

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

credit from the bank, a supply side argument. But there could be a demand side effect as well. Borrowers when offered a sub-optimal contract may choose to go somewhere else, changing the composition of borrowers that end up borrowing from the bank. Clearly, both stories are consistent with the information channel and it does not matter which one is operative, as they both are induced by a shift in the suppl. That being said, looking at branches where the degree of competition is low (borrowers have little choice), allows us to draw additional insights on the mechanism at work.

We have so far argued that a change in organizational design affects only the hierarchy of decision making. However, it is plausible the other contemporaneous changes may also affect bank lending. For example, an increase in level of a branch also brings in a higher level officer. To the extent that the higher level officer has better ability and experience, this may confound inference. Clearly, higher ability of the loan officer would generate the opposite results to the effect documented in the paper. We do a host of other robustness tests and discuss some alternate stories in Section 7. All in all, the results provide strong support for the view that organizational hierarchy affects the ability of banks to produce information.

This paper adds to the literature on organizational hierarchy and information production (Aghion and Tirole, 1997; Stein, 2002).[2] These theories analyze the trade-off in delegating decision-making to the agent. On the one hand, delegating a task leads to better 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 may hurt the principal. In these models, the higher the degree of congruence between the principal and the agent is, the more likely the principal is to delegate decision-making to the agent. An important insight from this theory is that the likelihood of interference dulls the incentives of the agent to exert effort.

Stein (2002) puts the above discussion in the context of communicating information within a loan approval process inside a bank. He argues that decentralized banks are more attractive when information about investment projects is subjective (i.e., 'soft') and cannot be credibly conveyed. Thus, such banks would be a poor fit for informationally

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

opaque borrowers such as small businesses. Confirming the theoretical predictions, our results suggest that the lower effort, induced by the hierarchical organizational design, leads to more standardization of loans and rationing of "soft information" loans. Furthermore, this standardization leads to a reduction in performance of loans.

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 depositors and small businesses, borrowers being particularly dependent on subjective information.[3] In particular, our work is closest to Liberti and Mian (2009) and Canales and Nanda (2012), who show that more hierarchical organizational structures tend to rely more heavily on hard, factual information about the borrower. What is unique about our setting 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. This allows us to strengthen further the identification strategy and nail down the channel through which organizational hierarchy affects production of information.[4]

The 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; Mian, 2006; Fisman et al., 2012; Agarwal and Hauswald, 2010). 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 we study. In Section 3, we present the baseline empirical specification for the analysis. Section 4 presents our results on soft information, loan performance, and lending quantity; Section

[3]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); Liberti et al. (2012).

[4]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.

6 discusses the other results of a more hierarchical organizational structure; Section 7 rules out a battery of alternate explanations. In Section 8, we conclude.

# 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 its branches.[5] At the contract level, it includes the loan balance outstanding, the interest rate, the maturity, type of collateral, collateral value, the number of days late in payment among others. 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. The sample spans 29 quarters – 1999 Q1 to the 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.[6]

The average branch lends to 24 new customers 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. In addition, the average rupee-weighted return on loans is 7.0 percent. Moreover, 90 percent of all loans are secured

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

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

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.

## 2.2 Organizational Design

Figure (2) provides an illustration of the managerial hierarchy of the bank. In total there are eight management levels with employees at each layer 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 within 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 viewed 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 fixed by the central office. For instance, all home improvement loans pay the same interest rate as car loans of maturity 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 deems fit. As a general rule, the larger the branch is, the more senior is the rank of the official heading it. In total, there are three branch structures (see Figure

(4), for time-series distribution see Figure (5)). The smallest branch (level 1) is typically headed by a branch manager, the next higher branch (level 2) is headed by a senior branch manager and finally the level 3 branch is overseen by a chief manager. Higher level branches have more layers of hierarchy associated with it. For example, the level 1 branch would generally have only one additional layer (loan officers) and the branch manager directly interacts with the borrowers. However, a level three branch would have three layers: loan officers, managers, and senior managers.

The lending process is quite simple. 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 agrees 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 approval limit of the loan officer, it goes to the next higher authority for approval. If the requested loan is even above the discretionary powers of the branch manager, the loan application along with the assessment of the branch is forwarded to a more senior manager either in regional, zonal, or the central office. Nevertheless, the decision of whether to reject or send the application for approval outside the branch rests 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 by both delinquencies and returns. That said, it should be noted that those cross-sectional patterns may be driven by the heterogeneity in types of borrowers in different branches. For instance, higher-level branches may be located in areas with more economic activity and 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 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 may be motivated through possible promotion to a higher rank manager. Whether an officer or a manager is nominated for a promotion depends on the annual evaluation and the tenure at the bank. A promotion generally is accompanied with a transfer to a new branch.

# 3 Empirical Specification

Our identification strategy employs a branch restructuring policy that is driven by predefined rules. A given branch is upgraded (degraded) if over the last two years the average outstanding balance of the combined loans and deposits exceeds (falls below) a fixed cut-off. In the event of upgradation, a branch is allocated more resources, including more personnel to meet the rising demand for services in that district. To manage the larger workforce, the branch's organizational hierarchy is also adapted by adding an additional layer of managers (see Figure (6)). Besides all that, the approval limit of the head of the branch is increased as well. 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 or roughly a fifth of all branches were reorganized (see Figure (7)).

There are a few points we want to highlight about the reorganization of branches. First, 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. Second, we would like to stress again that we are examining the loans that are eligible across all branches, that is, we are looking at loans that are lower than 5,00,000 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. Noteworthy to highlight, most of the branches that we examine have loan approval limits that are way above this cut-off, 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 differences-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 layers) branches, respectively. The branch fixed effects ($\tau_b$) control for fixed differences between treated and non-treated branches. The quarterly dummies ($\tau_q$) control for aggregate fluctuations. 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 $\delta$ 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 that is plausibly uncorrelated with the demand for credit, 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 (adding district interacted with quarter fixed effects) does not affect our results.

The approach can be understood with the following example. Suppose 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 what the effect of the upgrade is 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 things, 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 those 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

We now report the results, based on our empirical strategy discussed above. In section 4.1, we evaluate the effect of organizational design on total loans and the number of borrowers. Next, in section 4.2, we explore how hierarchy affects the performance of loans as measured by the delinquencies; and in section 4.3, we examine the effect of hierarchy on return on loans to the bank.

## 4.1 Lending

In this subsection, we explore the effect of organizational design on lending. We turn to our DID specification, defined in equation (1). As discussed previously, we use a branch office reorganization policy as a perturbation to the organizational hierarchy of a branch to make causal inferences about the effects of organizational hierarchies on loan outcomes. In particular, we look at the outcomes on the same set of loans in branches that changed the organizational design, comparing them against branches that did not. Looking at within-branch variation allows us to control for the branch-specific, unobservable characteristics, thus mitigating the concern of endogenous choice of organizational structure. Besides, a control group, active in the same line of business and subject to the same institutional rules and environment, is well suited to capture the aggregate time trends.

Columns 1 to 3 in Table (3) report the effect of the organizational design on the loan quantities, estimated using the differences-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).

In columns 4 to 6, we further investigate issues of reverse causality that might be driving the quantity effect and hence the change in the organizational design. 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. A way to address this and similar other concerns is to study 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: $\text{Before}^2$ is a dummy variable that equals one (minus one) for a branch that will be upgraded (downgraded) in one or two quarters; $\text{Before}^0$ is a dummy variable that equals one (minus one) if the branch is upgraded this or one quarter ago; $\text{After}^2$ is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago; and $\text{After}^{4+}$ is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) four quarters ago or more. The variable $\text{Before}^2$ 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 other factors than organizational design. In fact, the estimated coefficient on the $\text{Before}^2$ is economically small and statistically insignificant. Furthermore, we find that the coefficient on the $\text{Before}^0$ is smaller than those on the $\text{After}^2$ and $\text{After}^{4+}$, suggesting that the documented effect persists in the long run.

## 4.2 Loan Repayment

We next examine how a change in hierarchy affects the quality of loans originated by the bank. We examine loan delinquencies, where a loan is classified as delinquent if it is 60 or more days late in payments within a year since its origination. We then aggregate the loan level default measure and obtain a branch-quarter delinquency rate, i.e., the fraction of newly issued loans that are delinquent within a year since the inception. In Table (4), columns 1 and 2 examine the effect of organizational design on equally- and value-weighted loans, respectively. The regression specification uses the differences-in-differences methodology, defined in equation (1).

We find that an increase in hierarchy increases delinquencies for the same set of loans, evaluated before and after the reorganization. The coefficients on the *Branch Level* are economically large and statistically significant at 1 percent both for equally- and value-weighted default rates. 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 equally-weighted measure is 1.0 percent, corresponding to a 20 percent increase relative to the mean. Addressing reverse causality and trend concerns, a study of the dynamic effects of the organizational design (columns 4 and 5) indicates that there is no sign of an increase in the default rates two quarters prior to the change. An important finding is the significant difference between the value- and equally-weighted measures (column 3). 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.

## 4.3 Return on Loans

Thus far, we have shown that more centralized organizational hierarchy leads to contract standardization 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 one side, increasing default rates put a downwards pressure on the returns. On the other side, factors such as the recovery rates might alleviate these effects on return.

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 $q$. At first, we calculate the lifetime ROL for each loan separately and only then aggregate the loan-level returns at the branch-quarter level. The return on loans, representing earnings of the bank per rupee lent during the lifetime of a loan, is given as follows:

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

where $\omega_{b,i,\tilde{q}} = \frac{\mathrm{Loan}_{b,i,q}}{\sum_{\tilde{q}=q}^{\bar{q}} \mathrm{Loan}_{b,i,\tilde{q}}}$ 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., the outstanding loan amount is higher. Besides, if a loan defaults towards the end of the repayment period, when only a fraction of the loan remains unpaid, we protect ourselves from overestimating the effect of the loss given default. All in all, the value-weighted ROL is a better measure for estimating the real impact on branch's performance than the equally-weighted measure.

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

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

where $\eta_{age_i}$ 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:

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

where $\sigma_{age_i}$ 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, 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. Importantly, 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. Hence, for robustness we also check our results using three other recovery rates:[7] 25 percent as suggested by the Doing Business Database of the World Bank, a pessimistic 15 and an optimistic 50 percent. The results remain qualitatively the same.

Using the main DID specification, we find that the return on the same set of loans reduces after a branch becomes more hierarchical (Table (6)). The point estimates suggest

[7]The results are available upon request.

that after the introduction of an additional managerial layer the return on an individual loan decreases by 100 basis points (column 2). The economic effect is huge. 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 points fall in return (column 1) is equivalent to a 10 percent slide in the branch's performance. Further, the estimated results do not have any pre-trend (columns 4 and 5), 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 3) further fortifies the friction in information production: the return on large loans shrinks more, suggesting a worse allocation of resources in the more hierarchical structure.

# 5 Alternate Approach

The results so far support the view that an increase in organizational hierarchy reduces banks ability to produce information and affects credit allocation. 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. (2013). 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 a higher loan amount to the good borrower and a lower to the bad one. Thus an increase in information would be captured in an increase in dispersion of contract terms. This is the basic intuition behind the test. By examining the second moment of contractual terms, one can measure the amount of soft information content on the loans. 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 will 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 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. (2013).

## 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 differences-in-differences methodology defined in specification (1), both measures deliver qualitatively 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. Lastly, in columns 3 and 4, we investigate the dynamic effects and find no pre-trend. In fact, both pre-trend coefficients are of opposite sign if anything. Moreover, all of the effects increase over time and persist in the long run. Thus, the result on soft information remains robust to concerns such as reverse causality.

## 5.2 "Quasi" R-square

For the second approach we use a two-stage estimation procedure.[8] 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 is, the lower is 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 - $\tau_b$ and $\tau_q$ - capture the time invariant components of each branch and aggregate 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 is, the larger is the loan amount. Specifically, raising the collateral by 10 percent would increase the loan amount by roughly 0.9 percent. Similarly, the longer the maturity or the higher the interest rate

[8] We could have alternatively done this test in one step, by calculating the R-square on loan quantity by every branch in every quarter. Unfortunately, for large number of branches, there are very few new loans that are originated every quarter, making the model fit the data perfectly.

is, the larger is the loan size. Additionally, female borrowers, representing 17 percent of the sample, take loans that are, on average, 13 percent smaller than those taken by male borrowers. The adjusted $R^2$ of the regression is 0.55, which leaves 45 percent of the credit model unexplained, therefore implying that the bank's credit decisions comprise of roughly 45% subjective information.

Graphically 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.[9] 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 the two density functions to be different with 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 control for geographic characteristics as well. Thus, in addition to the 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 the commonalities in 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 manage-

[9] The residuals are standardized to account for the heterogeneity in the pool of borrowers across branches. To understand why better, imagine the following situation. The distribution of granted loans in branch A is wide (i.e., large standard deviation) due to large heterogeneity amongst 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; nevertheless, it is not true. 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.

rial 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 (columns 5 and 6 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. Hence, the agency problems between the manager of the branch and the loan officer are strong. This finding again confirms that a hierarchical structure leads to distortions in information production.

In column (6), we further investigate issues of reverse causality that might be driving the contract standardization and hence the change in the organizational design. We find that the estimated coefficient on the $\text{Before}^2$ is economically small and statistically insignificant, meaning that there is no pre-trend in the data. Furthermore, the coefficient on the $\text{Before}^0$ is smaller than those on the $\text{After}^2$ and $\text{After}^{4+}$, suggesting that the loan standardization amplifies over time and remains significant.

# 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 enable the approval of more loans 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. 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. 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 decide over the loans internally then.

Since after an upgrade the head of a branch can act on her soft information, we find an improvement in the lending outcomes on large loans (see Table (10)). First, 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 ensures that quarters without loans do not become missing values. Second, 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). Third, 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 qualitatively the same results. As the results for small loans are qualitatively the same for all measures of soft information, we conjecture that the same must hold 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 done internally (column 1), and the probability of issuing a large loan increases by 3.5 percentage points (column 2). The latter result is equivalent to an 85 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. To conclude, 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, from a social point of view, the net effect is ambiguous as small borrowers lose while large gain.

## 6.2 Competition

We next examine the effect of bank competition on our results. We measure branch density as the log of the total number of branches per 1,000 inhabitants at the district level in year 2001, obtained from the Reserve Bank of India.[10] 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 (11). While our results are present across the spectrum of bank competition, they all – soft information, returns, defaults and quantities – are particularly strong in more competitive banking markets (see Table (11)). 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.

The cross-sectional test with competition also allows us to disentangle supply side- from demand-side effects. Specifically, it is argued that more hierarchical structures reduce a bank's ability to produce information on loans. This would change the allocation of credit from the bank, a supply side argument. But there could be a demand side effect as well. Borrowers when offered a sub-optimal contract may choose to go somewhere else, changing the composition of borrowers that end up borrowing from the bank. Clearly, both stories are consistent with the information channel and it does not matter which one is operative, as they both are induced by a shift in the supply. That being said, looking at branches where the degree of competition is low (borrowers have little choice), allows us to draw additional insights on the mechanism at work.

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

# 7 Alternate Explanations and Robustness Tests

We have so far shown that a change in organizational design affects banks ability to produce information on loans that it generates and has implications for capital allocation decision by banks. While we are labeling the change in organizational design as primarily a chance in organizational hierarchy, there are other changes to organizational design that can potentially confound inference. We discuss these changes in this section and discuss specific ways to rule them out.

## 7.1 New Officer Effect

A change in organizational design also brings in a new official as the head of the branch. In case 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, has access to a more knowledgeable advisor now. It should be noted that such an effect, if present, would lead to a higher soft information and lower defaults on loans, thus biasing against finding the result that we have identified in the paper.

In a similar vain, one could argue that the arrival of a new branch manager, something that accompanies changes in organizational design, leads to a temporary loss in information and that is what drives the poor performance of loans and higher standardization (a new officer tends to over-rely on hard information). This is not true for two reasons. First, such an effect should also be present, and perhaps to a higher degree, when officers are rotated without the change in organizational design. We do not find this to be the case (see Table (13)). Second, 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.

## 7.2 Manipulation

As noted earlier the reorganization of a branch entails a change in the loan approval limit. This change in the cut-off may alter the composition of borrowers around the cut-off. To see this clearly, consider the following situation. An individual with no credit history or adverse credit history requests a loan for 11,000 USD from a manager whose approval limit is only 10,000 USD. Even though after a thorough investigation the manager knows that the borrower is 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 10,000 USD 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 that branch does not face this dilemma (if the approval limit is above 11,000 USD) as he can approve that loan within the branch. He would then simply approve the 11,000 USD loan. Thus manipulation of loan amount may change the composition of borrowers around the threshold.

To show this does not affect our results, we perform some additional tests. We begin by plotting the Epanechnikov kernel density functions around the normalized cut-off for pre- and post-treatment periods (Figure (10)). As can be seen in Figure (10), both distributions are statistically the same around the cut-off 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.[11] We next throw out loans that are within 20 percent window around the cut-off[12] and re-estimate our specification. Our results remain virtually the same with the lower approval limit (Table (12)). Finally, as noted earlier, the smallest common cut-off is binding for only a subset of bank branches (roughly a sixth of the branches). Excluding those branches leaves our results qualitatively unchanged. In sum, all three tests allay all concerns of manipulation around the cut-off.

[11] The humps in the distribution represent round numbers that are popular loan amounts such as 10,000 and 15,000.

[12] For example, if the cut-off is 10,000 USD then all loans from 8,000 to 10,000 would not be considered.

### 7.3 Other "Shocks"

We have so far assumed that the change in organizational design affects only the supply side of loan granting process. However, it is plausible that our results may be driven by local contemporaneous demand shocks, for example. Alternatively, a change in the degree of bank competition may have forced banks to change their organizational structure. To account for these and similar other concerns, we saturate our main specification by including interacted quarter-district fixed effects. This approach splits our sample in 362 geographical units and controls for all time variation within those districts. As a result, we exploit the within-district variation between treated and non-treated branches. To the extent that such shocks affect all branches at a district level, such shocks get differenced out in our specification. As can be seen (Table (14)), saturating the specification does not affect the qualitative nature of our results.

## 8 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 exist 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. Further, 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. Our paper also shows that large organizations mitigate the problem of transmitting soft information through creating within-firm sub-organizations. Although in line with Stein's (2002) view that more hierarchical firms tend to base their decision 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 to reduce this problem.

It is important to note that while this paper identifies the effect of hierarchy on information production, 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 those branches? This is an important question for future research.

Finally, this paper does not make any efficiency claims either. While we show that hierarchy induces negative effects for smaller loans, larger loans do much better in such branches. Thus, the efficiency implications are ambiguous.

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

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

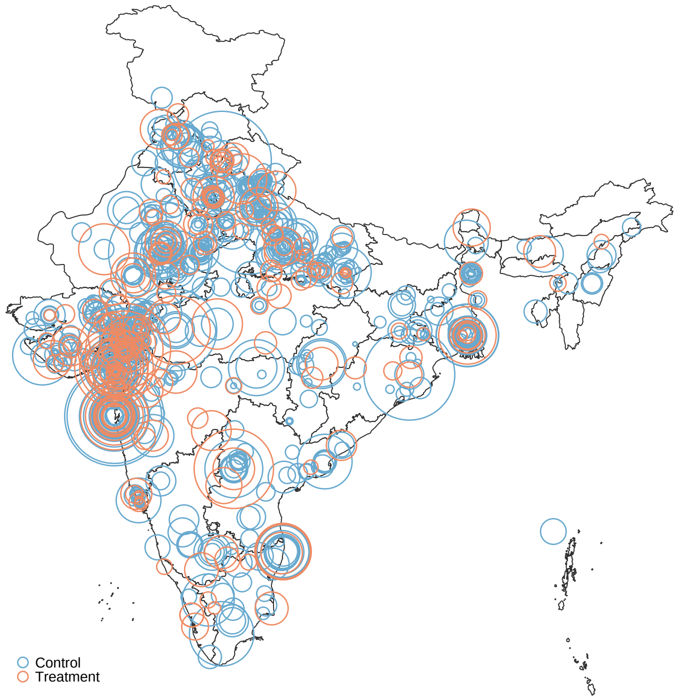



**Figure 2:** Organizational Design

The bank's organizational design consists of ten layers described below. A more highly ranked manager carries more decision power and authority. The top five layers, marked with an asterisk, are the senior management team, mainly involved with the business development. The lower three focus on operation 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. In case the loan falls out 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.

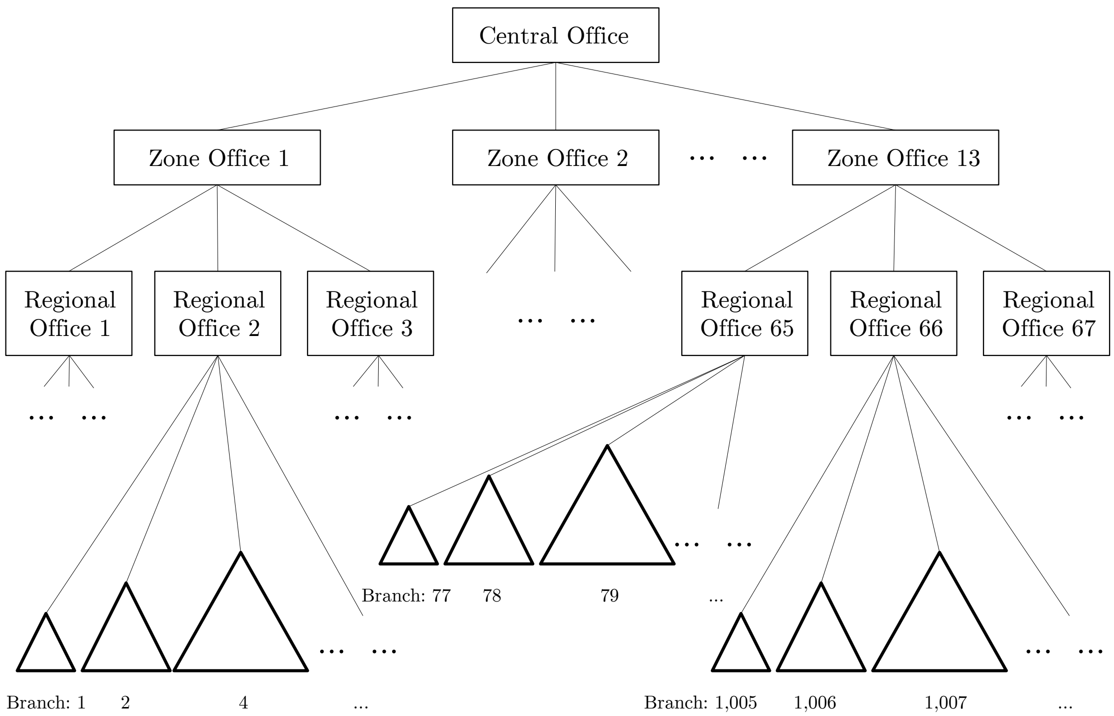



**Figure 4:** Branch Office Design

Below is a schematic illustration of the bank's branches. Each level has a specified approval limit on the size of the loan. In case the loan falls out 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).

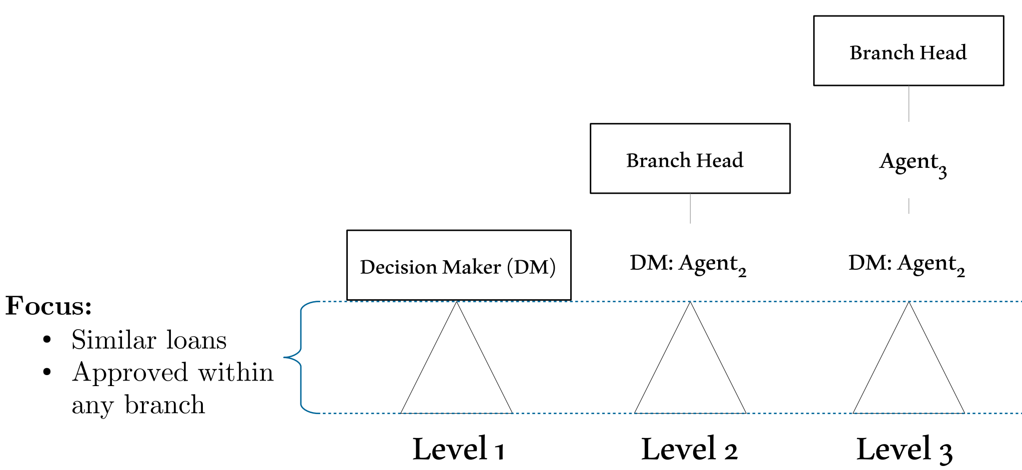


**Figure 5:** Distribution of Branch Levels

The chart below plots the time series distribution of branch levels. In total we have roughly 2,500 branches.

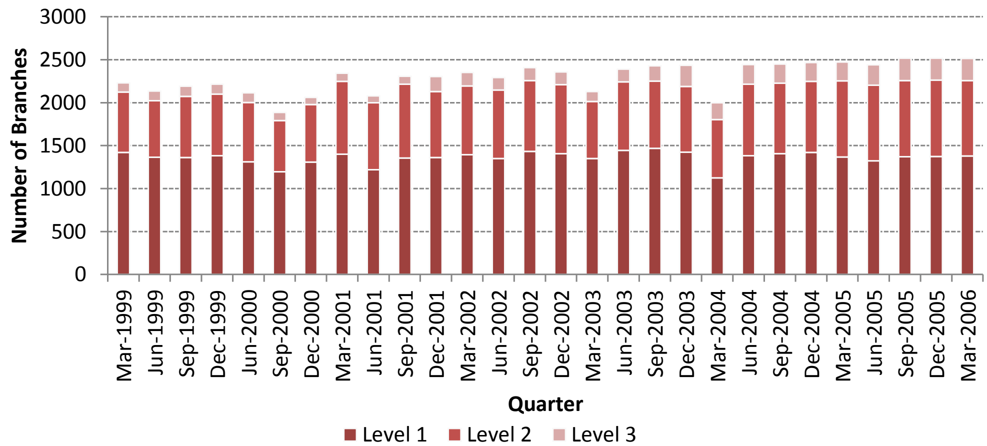
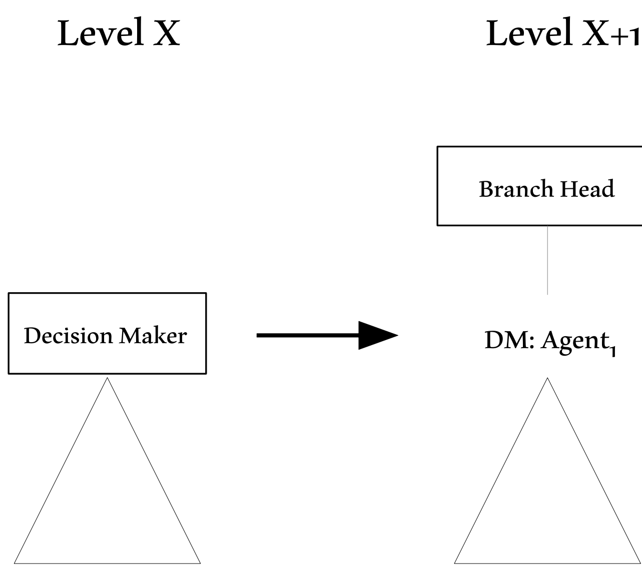


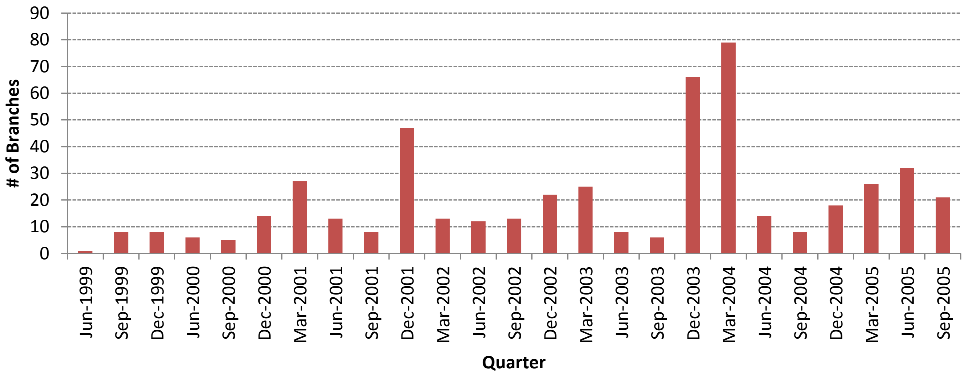

**Figure 6:** Identification Strategy

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

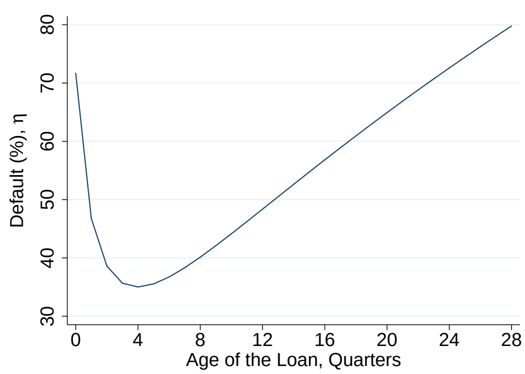
Below we plot the distribution of branch level changes over time. In total 500 branches (or roughly 20% of total) were reorganized.




## **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.

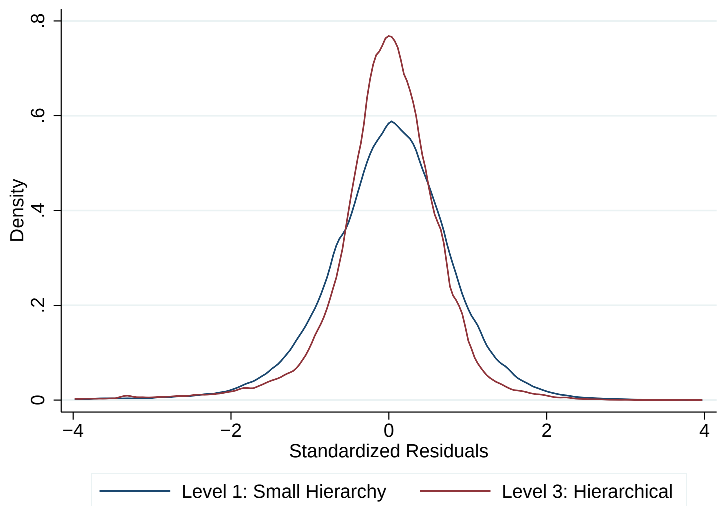



**Figure 10:** Distribution Around the Approval Threshold

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.

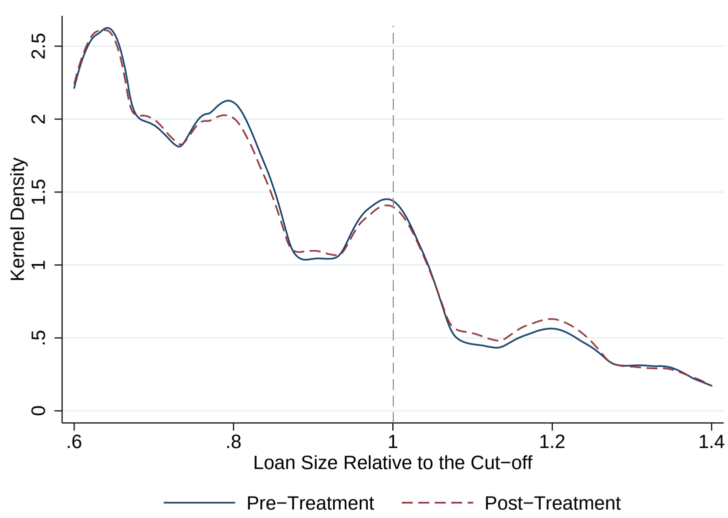


**Table 1:** Summary Statistics

The 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

The 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

The table reports the effect of organizational design on total new lending to small individual borrowers (columns 1 and 4), number of new individual borrowers (columns 2 and 5), and loan size (columns 3 and 6), 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. $\text{Before}^{-2}$ is a dummy variable that equals one (minus one) if the branch is upgraded (downgraded) in one or two quarters. $\text{Before}^{0}$ is a dummy variable that equals one (minus one) if the branch is upgraded this quarter or one quarter ago. $\text{After}^{2}$ is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. $\text{After}^{4+}$ 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%

| Dependent Variable | $\ln\left(\text{New Ind. Debt}_{b,q}\right)$ | $\ln\left(\text{\# of brwrs}_{b,q}\right)$ | $\ln\left(\overline{\text{Loan}}_{b,q}\right)$ | $\ln\left(\text{New Ind. Debt}_{b,q}\right)$ | $\ln\left(\text{\# of brwrs}_{b,q}\right)$ | $\ln\left(\overline{\text{Loan}}_{b,q}\right)$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Branch Level | -0.099*** | -0.045* | -0.054*** | | | |
| | (0.030) | (0.025) | (0.017) | | | |
| $\text{Before}^{-2}$ | | | | 0.032 | 0.039 | -0.006 |
| | | | | (0.040) | (0.032) | (0.024) |
| $\text{Before}^{0}$ | | | | -0.037 | 0.014 | -0.051** |
| | | | | (0.041) | (0.033) | (0.024) |
| $\text{After}^{2}$ | | | | -0.123*** | -0.055 | -0.068*** |
| | | | | (0.043) | (0.034) | (0.026) |
| $\text{After}^{4+}$ | | | | -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 |
| Adj-$R^2$ | 0.396 | 0.450 | 0.403 | 0.396 | 0.450 | 0.403 |
| Branch FE | Y | Y | Y | Y | Y | Y |
| Quarterly FE | Y | Y | Y | Y | Y | Y |

**Table 4:** Effect of Organizational Design on Loan Repayment

The table reports the effect of organizational structure on loan repayment (columns 1 and 2) and its dynamics (columns 4 and 5) using specification (1). Column 3 reports the difference between the estimated coefficients on equally- and value-weighted default rates. Defaults are measured as a fraction of loans that are late over 60 days 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 is 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. 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. P-values reported in the square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

| | Defaults (60+ days late) | | | | |
|---|---|---|---|---|---|
| | Equally Weighted | Value Weighted | Difference (2)-(1) | Equally Weighted | Value Weighted |
| | (1) | (2) | (3) | (4) | (5) |
| Branch Level | 0.010*** | 0.014*** | 0.004*** | | |
| | (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 |
| Adj-$R^2$ | 0.234 | 0.183 | | 0.234 | 0.183 |
| Branch FE | Y | Y | | Y | Y |
| Quarterly FE | Y | Y | | Y | Y |

**Table 5:** Recovery Rates

The table below reports mean (1) and the standard error (2) of our estimated recovery rates that are used in return on loan calculations. Besides, 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<br>(1) | S.E.<br>(2) | Obs.<br>(3) |
|---|---|---|---|---|
| Recovery rate ($\delta$) | 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 and 2, respectively) and its dynamics (columns 4 and 5) using specification (1). Column 3 reports the difference between the estimated coefficients on equally and value-weighted returns. The unit of analysis is branch-quarter return on loans. At 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 is 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. 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 the parentheses are corrected for clustering at the branch level. P-values reported in the square brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

| | | | ROL | | |
|---|---|---|---|---|---|
| | Equally Weighted | Value Weighted | Difference (2)-(1) | Equally Weighted | Value Weighted |
| | (1) | (2) | (3) | (4) | (5) |
| Branch Level | -0.007*** | -0.010*** | -0.003** | | |
| | (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 |
| Adj-$R^2$ | 0.155 | 0.136 | | 0.155 | 0.136 |
| Branch FE | Y | Y | | Y | Y |
| Quarterly FE | Y | Y | | Y | Y |

## Table 7: Measures of Soft Information

The table reports the effect of organizational design on soft information: inter-quartile range of debt (columns 1 and 3) and standard deviation of debt (columns 2 and 4), estimated in 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. $\text{Before}^{-2}$ is a dummy variable that equals one (minus one) if the branch is upgraded (downgraded) in one or two quarters. $\text{Before}^{0}$ is a dummy variable that equals one (minus one) if the branch is upgraded this quarter or one quarter ago. $\text{After}^{2}$ is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. $\text{After}^{4+}$ 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%

| Dependent Variable: | $\ln\left(\text{IQR}_{b,q}\right)$ | $\ln\left(\sigma_{\text{Loan}_{b,q}}\right)$ | $\ln\left(\text{IQR}_{b,q}\right)$ | $\ln\left(\sigma_{\text{Loan}_{b,q}}\right)$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Branch Level | -0.123*** | -0.095*** | | |
| | (0.026) | (0.021) | | |
| $\text{Before}^{-2}$ | | | -0.026 | 0.020 |
| | | | (0.040) | (0.032) |
| $\text{Before}^{0}$ | | | -0.135*** | -0.050 |
| | | | (0.042) | (0.034) |
| $\text{After}^{2}$ | | | -0.111*** | -0.102*** |
| | | | (0.039) | (0.035) |
| $\text{After}^{4+}$ | | | -0.145*** | -0.117*** |
| | | | (0.034) | (0.027) |
| Observations | 54,079 | 54,079 | 54,079 | 54,079 |
| Adj-$R^2$ | 0.271 | 0.291 | 0.271 | 0.291 |
| Branch FE | Y | Y | Y | Y |
| Quarterly FE | Y | Y | Y | Y |

**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 the 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 the branch $b$, 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. The coefficients in column (6) report the cumulative dynamics of the organizational change. Before$^{-2}$ is a dummy variable that equals one (minus one) if the branch is 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. 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 the 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) |
| Branch Level | -0.048*** | -0.042*** | -0.038*** | -0.043*** | -0.033*** | |
| | (0.003) | (0.004) | (0.004) | (0.006) | (0.008) | |
| 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 |
| Adj-$R^2$ | 0.02 | 0.03 | 0.04 | 0.04 | 0.110 | 0.110 |
| Initial Level FE | N | N | N | Y | N | N |
| Zone FE | N | Y | N | N | N | N |
| Region FE | N | N | Y | Y | N | N |
| Branch FE | N | N | N | N | Y | Y |
| Quarterly FE | Y | Y | Y | Y | Y | Y |

**Table 10:** Effect of Organizational Design on Large Loans, Eligible for Approval Internally

The 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 after 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. $\text{Before}^{-2}$ is a dummy variable that equals one (minus one) if the branch is upgraded (downgraded) in one or two quarters. $\text{Before}^{0}$ is a dummy variable that equals one (minus one) if the branch is upgraded (downgraded) this quarter or one quarter ago. $\text{After}^{2}$ is a dummy variable that equals one (minus one) if the branch was upgraded (downgraded) two or three quarters ago. $\text{After}^{4+}$ 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 | 0.465*** | 0.035*** | 0.067*** | | | |
| | (0.106) | (0.008) | (0.015) | | | |
| $\text{Before}^{-2}$ | | | | 0.142 | 0.012 | 0.031 |
| | | | | (0.121) | (0.009) | (0.023) |
| $\text{Before}^{0}$ | | | | 0.108 | 0.009 | 0.026 |
| | | | | (0.125) | (0.009) | (0.022) |
| $\text{After}^{2}$ | | | | 0.420*** | 0.033*** | 0.067*** |
| | | | | (0.148) | (0.011) | (0.023) |
| $\text{After}^{4+}$ | | | | 0.633*** | 0.047*** | 0.093*** |
| | | | | (0.136) | (0.010) | (0.021) |
| Observations | 54,079 | 54,079 | 54,079 | 54,079 | 54,079 | 54,079 |
| $\text{Adj}-R^2$ | 0.101 | 0.097 | 0.076 | 0.101 | 0.097 | 0.076 |
| Quarter FE | Y | Y | Y | Y | Y | Y |
| Branch FE | Y | Y | Y | Y | Y | Y |

**Table 11:** Bank Competition

The 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 an outlier district that corresponds to 3% of the sample. The standard errors are reported in the parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

| | Soft info | $\ln\left(\mathrm{IQR}_{b,q}\right)$ | $\ln\left(\sigma_{\mathrm{Loan}_{b,q}}\right)$ | VW ROL | VW Defaults | $\ln(\text{New Ind. Debt}_{b,q})$ | $\ln(\text{\# of brwrs}_{b,q})$ |
|---|---|---|---|---|---|---|---|
| | (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 12:** 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 late over 60 days 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 is 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. 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%

| | 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 |
| Quarterly FE | Y | Y | Y | Y |

## **Table 13:** 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), log total new individual borrowers (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 late over 60 days one year forward. The standard errors are reported in the parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

| | Soft Info | VW ROL | VW Default | $\ln\left(\overline{\text{Loan}}_{b,q}\right)$ | $\ln$ (New Ind. Debt$_{b,q}$) | $\ln$ (# of brwrs$_{b,q}$) | $\ln\left(\text{IQR}_{b,q}\right)$ |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Change | -0.015 | -0.004 | 0.001 | 0.007 | -0.029 | -0.036 | 0.014 |
| | (0.010) | (0.004) | (0.003) | (0.744) | (0.037) | (0.029) | (0.036) |
| Obs | 50,548 | 50,548 | 50,548 | 50,548 | 50,548 | 50,548 | 50,548 |
| Adj-$R^2$ | 0.109 | 0.130 | 0.181 | 0.388 | 0.396 | 0.444 | 0.264 |
| Branch FE | Y | Y | Y | Y | Y | Y | Y |
| Quarterly FE | Y | Y | Y | Y | Y | Y | Y |

## **Table 14:** Saturated Specification

The table reports the results of saturated specification where instead of quarterly fixed effects we include interacted quarter-district fixed effects. 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), log total new individual borrowers (column 6), and the inter-quartile range of debt (column 7). 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 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 late over 60 days one year forward. The standard errors are reported in the parentheses and clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

| | Soft Info | VW ROL | VW Default | $\ln\left(\overline{\text{Loan}}_{b,q}\right)$ | $\ln$ (New Ind. Debt$_{b,q}$) | $\ln$ (# of brwrs$_{b,q}$) | $\ln\left(\text{IQR}_{b,q}\right)$ |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Branch Level | -0.022** | -0.006*** | 0.009*** | -0.052*** | -0.083** | -0.031 | -0.112*** |
| | (0.009) | (0.002) | (0.003) | (0.018) | (0.033) | (0.026) | (0.029) |
| Obs | 54,079 | 54,079 | 54,079 | 54,079 | 54,079 | 54,079 | 54,079 |
| Adj-$R^2$ | 0.138 | 0.207 | 0.271 | 0.444 | 0.464 | 0.539 | 0.298 |
| Branch FE | Y | Y | Y | Y | Y | Y | Y |
| Quarter-District FE | Y | Y | Y | 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 among 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 | |