Estimating The Effect Of Hierarchies On Information Use

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Abstract

Theory suggests that greater hierarchical distance between a subordinate and his boss makes it more difficult to share abstract and subjective information in decision making. A novel data set put together from credit dossiers of large corporate loan applicants enables us to observe the information collected by loan officers and also how it is used by the ultimate loan approving officer. We find that greater hierarchical distance between the information collecting agent and the loan approving officer leads to less reliance on subjective information and more on objective information. By exploiting non-linearities in the "assignment rules" that determine an applicant's hierarchical distance, and using information collecting agent fixed effects, we show that our result cannot be driven by endogenous assignment of applicants. We also find that higher frequency of interactions between the information collecting agent and loan approving officer, both over time and through geographical proximity, helps mitigate the effects of hierarchical distance on information use. Our results show that hierarchical distance influences information use, and highlight the importance of "human touch" in communication.

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Does organizational design effect the sharing of information within a firm? The evolution of firms from family businesses to large hierarchical organizations has sparked an extensive theoretical literature that links the ability of organizations to share information with the design of hierarchies (Aghion and Tirole 1997; Bolton and Dewatripont 1994; Dewatripont and Tirole 2005; Garicano 2000; Garicano and Rossi-Hansberg 2006; Radner 1993; Stein 2002). However empirical understanding of whether such a link exists remains extremely limited. There are statistical difficulties in measuring theoretical constructs such as "information", and empirical hurdles in finding plausibly exogenous variation in organizational design. We provide evidence from banking on how *hierarchical distance*, i.e. distance between a loan approving officer and his subordinate who collects information, effects the type of information used in decision making.

A number of theories suggest that private non-verifiable information, e.g. subjective information, is difficult to use across organizational layers.[1] The precise channels vary from *ex-ante incentives* for information collection (Aghion and Tirole 1997; and Stein 2002), to *strategic manipulation* of information (Crawford and Sobel 1982) and *ex-post communication costs* (Sah and Stiglitz 1986; Radner 1993 and Bolton and Dewatripont 1994). However regardless of the underlying channels, these papers share the common prediction that hierarchical distance makes it difficult to use subjective information, hence increasing reliance on objective information.

Testing such predictions requires one to observe the flow of information within an organization and also to have plausibly exogenous variation in the hierarchical distance travelled by the decision making process. It has been extremely difficult to meet these requirements in the past. This paper uses data from the loan approval process that offers a natural environment for testing the impact of hierarchical distance on information use.

Our methodology can be understood from the following representative example. Consider a loan officer who receives a firm's loan application, and then collects a variety of information about the firm. For simplicity, summarize this information into a subjective signal (S) that represents the loan officer's personal assessment of the firm (e.g. an "A" in "management professionalism"), and an objective signal (H) representing firm performance (such as a "10%" in ROA).

Suppose for now that the loan officer also has the authority to decide how much to lend to the

[1] Hayek (1945) was perhaps the first to formally emphasize the role that subjective information plays in decision making: "The sort of knowledge with which I have been concerned is knowledge of the kind which by nature cannot enter into statistics and therefore cannot be conveyed to any central authority in statistical form".

applicant. He will then infer the firm's inherent quality given the two signals and decide on the loan limit to approve. All else equal, higher firm quality should lead to higher loan approvals. Furthermore, define *informativeness* of a signal as its covariance with the underlying firm quality of interest. Then the loan officer will put weights β_S and β_H on the two signals in his loan approval decision, where the weights are proportional to the informativeness of the respective signals.

Next suppose that for some firms the loan officer cannot make the loan approval decision. Instead after collecting signals S and H for these firms, he must send the loan application "upwards" to his boss (the manager) for approval. Will the manager give the same importance to the two signals as the loan officer? The theoretical literature cited earlier suggests no. For example, knowing that he no longer has discretion over the final decision, the loan officer might put less effort in collecting S, hence reducing its informativeness (Aghion and Tirole 1997; Stein 2002). Alternatively he might strategically add noise to S (Crawford and Sobel 1982). Thus when signals S and H reach the manager, S would have lost part of its informativeness. The same is not true of H (i.e. audited financials) since this signal is verifiable. Hence weights $\beta_S^{'}$ and $\beta_H^{'}$ used by the manager will be such that $\beta_S^{'} < \beta_S$ and $\beta_H^{'} > \beta_H$. In other words, credit approved by the manager will be less sensitive to subjective and more sensitive to objective information compared to credit approved by the loan officer (see section I for full details).

We test this prediction using data from the credit dossiers of a large multi-national bank in Argentina. The data tracks the entire loan approval process for all 424 corporate loan applicants in the year 1998. It contains all of the information collected by a loan officer regarding an applicant, including subjective information such as the loan officer's impression about an applicant's management quality, as well as objective information such as audited firm financials. Moreover, there is variation in the hierarchical distance travelled by different loan applications. While some are approved at a low hierarchical level (including by the loan officer himself), others have to go higher up for approval.

We find strong support for the theoretical and empirical predictions highlighted earlier. Sensitivity of approved loan amount to objective information is much higher at higher levels of approval, while sensitivity to subjective information is significantly lower at higher levels of approval. However a key concern with this finding is that the differences in sensitivity to information might be spuriously driven by endogenous allocation of applicants to approval levels, or alternatively the endogenous allocation of applicants to loan officers collecting information. We separate these concerns into three categories.

The first is the *endogenous bank assignment* concern that applicants are assigned to different hierarchical levels for approval in a way that systematically affects the sensitivity of credit to information. For example, suppose larger firms have naturally more informative objective information and are also more likely to be sent higher up for approval by the bank. Then credit sensitivity to objective information will be higher for firms approved at higher levels because of the type of firms being sent higher up, not because of hierarchical distance. In general this concern is very difficult to address because bank assignment might be based on unobserved firm characteristics.

However the assignment principle chosen by the bank to assign firms to approval levels is based on observable applicant characteristics. The bank's credit manual prescribes a pre-specified set of rules that are a non-linear function of some observable firm characteristics such as applicant size, industry etc. We can thus exploit these non-linearities to provide a plausibly exogenous source of variation in hierarchical distance. We do so by controlling for linear and other higher powered functions of applicant characteristics that the bank uses in it allocation rules.

While the above controls for endogenous assignment by the bank, there is a related concern of *endogenous self-assignment* by loan applicants. The assignment of applicants to various hierarchical approval levels depends partly on firm attributes that an applicant has no control over (such as central bank credit history, industry etc.), but partly on attributes (such as loan maturity and requested amount) that an applicant clearly has discretion over. Hence a firm might strategically manipulate its application in order to get assigned to its desired approval level. For our purposes, self-assignment by applicants will be a concern if firms that self select into higher approval levels are also firms that naturally have more informative objective information (or less informative subjective information).

Our solution to dealing with endogenous self-assignment comes from the observation that any strategic deviation away from one's "true application" is costly. For example, requesting a shorter term loan when a firm requires longer term financing is going hamper a firm's investment policy. Thus firms attempting to self-assign in a level different from the one predicted by their true application, are likely to lie *at the margin* of high and low approval levels. We can thus account for possible self-assignment by dropping firms that lie on the margin between approval levels.

Finally there may also be an *endogenous loan-officer assignment* concern that firms that are approved at low levels (e.g. by loan-officers themselves) are assigned to better or more experienced loan officers that generate more informative subjective information due to their higher ability. If this were true, then the differential sensitivity across approval levels will be driven by differences in the ability of loan officers collecting information rather than any direct effect of hierarchical distance. However, we can completely account for this concern non-parametrically by using loan officer fixed effects appropriately. The fixed-effects strategy forces comparison across firms that are approved at different hierarchical levels but whose information is collected by the *same* loan officer.

Our result remains robust to controlling for all of these endogeneity concerns. Credit sensitivity to subjective information remains smaller, and credit sensitivity to objective information remains larger for firms approved at higher levels. Additional tests further bolster the case that our result is driven by features of organizational design rather than any spurious correlation.

We find that the change in information sensitivity at higher levels is not gradual. Loan approval process within our bank can have up to 5 hierarchical layers, and the change in information sensitivity (for both subjective and objective information) occurs suddenly between levels 2 and 3. Exploring this further, we find that these sharp changes in information sensitivity are driven by differences in the geographical location of bank officers. The change in credit sensitivity to information occurs only when the loan approving officer sits in a different geographical region than the loan officer.

The co-location result suggests that close proximity with the loan officer (who collects information) helps in communicating subjective information. The importance of repeated contacts is further strengthened as we find that the decline in sensitivity to subjective information at higher levels is smaller when information is generated by a more experienced loan officer. Higher level bank officers might be better able to understand, trust and "decode" subjective information from more experienced loan officers as a result of repeated interactions with them.

Finally, we decompose the aggregate index of subjective information into its constituent parts. This exercise reveals that the decline in subjective information sensitivity is larger for more subjective sub-components, reaffirming the interpretation that it is the subjectivity of a piece of information that makes it more difficult to use at higher hierarchical distances.

There is a vast theoretical literature related to many of the issues our paper touches upon, but a review is not feasible here. Overall our results are in line with the view that greater hierarchical distance discourages the use of subjective and more abstract information. Although we discuss possible interpretations at the end, we want to emphasize that our primary purpose is not to discriminate between various theories that might lead to this reduced reliance on subjective information.

Despite almost an explosion of work in the theory of organizations, empirical work has far lagged behind. Ours is one of the first papers that uses intra-firm data to directly test a key prediction of organizational theory. While there is some empirical literature that associates specialization of certain bank types to their organizational design (Berger et al 2005; and Mian 2006), the evidence that links organizational design to information use in these papers is indirect. In contrast, our paper provides a more direct test of the effect of hierarchical distance on information use.

I Information and Hierarchies

A number of papers investigate how hierarchies affect the acquisition, transmission and usage of information within an organization. A common theme that runs through this literature is that separation of tasks across organizational layers, such that employees in one layer rely on information generated by another, makes it more difficult to share information. We find it useful to categorize this literature into three classes:

(1) Incentive-based theories - Aghion and Tirole (1997) and Stein (2002) argue that large hierarchical systems inhibit the ex-ante incentives to collect information, particularly soft information. The drop in incentives occurs because employees in charge of collecting information cannot act on it and instead have to send information upwards for final decision. Given the "soft" nature of information, there is always a chance that it may be overruled or disregarded. Anticipation of such overrules reduces the incentives for investing in information collection effort.

(2) Strategic Manipulation of Information - The seminal work by Crawford and Sobel (1982) showed that senders of information will deliberately coarsify their information and make it noisier if their preferences are not perfectly aligned with those of the "receivers", who again have the authority to take final action.

(3) Ex-post Communication Costs- Work such as Radner (1993), Bolton and Dewatripont (1994) and Becker and Murphy (1993) focuses on the ex-post costs of communication, and argues that while hierarchies provide advantages such as specialization and parallel processing, they also bring trade-offs in the form of costly communication across hierarchical levels. Such costs are likely to be larger for subjective information that is harder to verify by third party.

While work cited above differs in its foundations, it shares a common theme. The literature predicts that introducing layers between employees generating information and those taking decisions, leads to difficulties in generating and transmitting information, particularly subjective information which is softer in nature. It is this particular prediction that we take to data in this paper. However, doing so is not straightforward since concepts like "informativeness" and "subjective information" must be defined empirically. We also need to pay particular attention to identification concerns. In particular, changes in the informativeness of information across hierarchical levels might be driven by omitted factors as opposed to hierarchies. We therefore provide a statistical framework for testing the theoretical predictions and then outline an identification strategy. Since the empirical section uses data from bank credit folders, we motivate our statistical framework using banking as an example.

A. Conceptual Framework

Consider a bank trying to decide how much to lend to a given firm. The bank is arranged as a hierarchy of two layers as shown in Figure I. A loan officer sits at the lower level and his manager at the higher level. The loan officer is responsible for receiving and reviewing each loan application. The review process involves collecting a variety of information about the firm. We summarize this information into two types: an objective signal H, and a subjective signal S. The objective signal consists of easily quantifiable information such as size, profitability and other audited financial ratios. The subjective signal on the other hand is more qualitative and includes information such as the loan officer's assessment of firm's management quality and project strength.

Once necessary information has been collected by the loan officer, there are two possible scenarios. Depending on the firm, either the loan officer has discretion to make the final credit approval decision, or he refers the case to his manager who then makes the final decision taking into account information collected by the loan officer.

Thus while information is always collected by the loan officer, there is variation in who has the final authority to approve the amount of loan to be issued to a firm. The credit approval decision (whether made by the loan officer or his manager) depends on quality Q of the firm, with higher Q firms receiving more credit. Q cannot be measured directly, but is inferred from information collected by the loan officer. In particular, signals H and S are used to infer quality Q of the firm as they are positively correlated with Q.

Given the above set up, the timing of the model is as follows. A firm with publicly observable prior Q_0 submits a loan application. The loan officer then reviews it and collects signals H and S

in the process. Once information is collected, the loan application gets sent to the credit approving authority (either loan officer or his manager). The loan officer knows ex-ante whether he has the final credit approval authority for the firm or not. The loan approving officer then updates his prior from Q_0 to Q_1, based on signals H and S, and gives the firm a loan of size $L(Q_1)$.

Both H and S are informative in figuring out the quality of the firm and hence how much to lend to it. We characterize the "informativeness" of these signals as their covariance with Q, and denote it by σ^2_{qh} and σ^2_{qs} respectively.

With informativeness defined, we can restate the key theoretical prediction in statistical terms. Theory predicts that as information travels up a hierarchy, subjective information loses informativeness more than objective information. In our statistical framework, a loss in informativeness of the subjective signal can be interpreted as a decline in σ^2_{qs} as signal S is communicated from lower to higher level. Let $\Delta\sigma^2_{qs}$ and $\Delta\sigma^2_{qh}$ be the decline in subjective and objective signals' informativeness when used at higher level. Then the theoretical prediction can be written as $\left|\Delta\sigma^2_{qs}\right| > \left|\Delta\sigma^2_{qh}\right|$. For simplicity and without any loss of generality, we can write this as:

$$\left|\Delta\sigma^2_{qs}\right| > 0, \text{ and } \left|\Delta\sigma^2_{qh}\right| = 0 \tag{1}$$

Intuitively, condition (1) says that the informativeness or precision of a subjective signal is higher when used by a loan officer who himself collected this information. On the other hand when subjective information is collected by a loan officer but used by his manager, its informativeness is lower. The same does not hold for objective information. Although objective information is also always collected by the loan officer, it does not lose its informativeness if used by the manager.

An example can help illustrate condition (1) further. Suppose objective signal H collected by a loan officer consists of ROA of a firm during the last 3 years, and is recorded as 20% from audited financials of the firm. Signal S on the other hand is a subjective score given by the loan officer regarding the quality of firm's new management and is recorded as an "A". If the loan officer has to communicate these two signals to the manager, the 20% ROA can be communicated without any loss of information. However, when grade "A" is communicated, it can lose part of its "informativeness" for reasons such as incentives or strategic manipulation. For example, incentive-based theories suggest that the loan officer might put in a lot of effort to collect more informative subjective information when he himself is the decision maker versus when he sends this information to his superior. Alternatively the loan officer might strategically coarsify his subjective information when it is used by his superior for reasons suggested by Crawford and Sobel (1982). In either case, an "A" going to a manager will have lower informativeness than an "A" used by a loan officer himself[2].

Given the statistical definition of subjective and objective information in (1) we can now formally investigate differences in the loan officer's and manager's credit approval decisions. The person making the final credit approval decision has to first form a posterior Q_1 on underlying firm quality Q. He then approves a loan of size $L(Q_1)$ based on the inferred Q_1.

In principle the loan-officer and manager could differ in their credit approval function $L(Q)$ - say because they have different abilities or face different incentives and costs. We will discuss in section V whether our results reflect differences between loan officers and managers in their ability or objective function. However, for now suppose loan officers and managers have the same credit approval function $L(Q)$, with $\frac{\partial L}{\partial Q} > 0$. Furthermore suppose Q, H, and S are all normally distributed with mean Q_0 and variances α_q^2 , α_h^2 and α_s^2 respectively.

Let $\widehat{X}$ denote the deviation of a variable X from Q_0. Then given signals H and S, the loan officer or manager will update his beliefs according to the updating equation:

$$\widehat{Q} = \beta_H * \widehat{H} + \beta_S * \widehat{S} \tag{2}$$

where β_H and β_S reflect sensitivity of the decision maker to the two signals and are given by, $\beta_H = \frac{\sigma_{qh}^2\sigma_s^2 - \sigma_{qs}^2\sigma_{sh}^2}{\sigma_h^2\sigma_s^2 - (\sigma_{sh}^2)^2}$ and $\beta_S = \frac{\sigma_{qs}^2\sigma_h^2 - \sigma_{qh}^2\sigma_{sh}^2}{\sigma_h^2\sigma_s^2 - (\sigma_{sh}^2)^2}$. The sensitivity of Q to a signal increases as its covariance with the signal goes up. There is also a "partialling out" effect: all else equal, higher covariance between one signal and Q decreases the sensitivity of Q to the other signal[3]. The definitions of subjective and objective information in (1), combined with equation (2) give us the following result:

Proposition 1 *Suppose subjective information loses "informativeness" when communicated to a higher level, while objective information does not, i.e.* $\left|\Delta\sigma_{qs}^2\right| > 0$, *and* $\left|\Delta\sigma_{qh}^2\right| = 0$. *Then sensitivity to objective information increases while that to subjective information decreases as credit is approved at a*

[2]There could be other reasons for the loss in informativeness of subjective signals. For example, aspects of firm management quality considered by the loan officer may not be the same as aspects considered by the manager when interpreting a grade of "A". Second even if no such discrepancy exists between the loan officer and manager, only the loan officer knows what an "A" really means in terms of exact quality attributes and how good of an "A" the firm has. In other words, quantifying subjective information into grades or scores naturally leads to a loss of content for a person other than the one who actually collected this information.

[3]Assuming subjective and objective information signals are positively correlated, i.e. $\sigma_{sh}^2 > 0$. This assumption is also very strongly met in our data.

higher level, i.e. $\beta_H^M > \beta_H^L$ *and* $\beta_S^M < \beta_S^L$*. where superscripts L and M refer to coeffecients for loan officer and manager respectively.*

In our analysis so far, we have assumed that loan officer and manager are risk neutral. Proposition 1 is further strengthened if loan officer and manager were risk averse. The reason is that loan officers who collect subjective information themselves will know more about a firm than the reported grades. For example, they will know more nuanced differences between two firms both with a subjective grade of "A". Thus the subjective signal will have a tighter variance for loan officers than managers. Since risk aversion punishes losses more harshly, for a unit increase in reported subjective information grade, managers will be more conservative than loan officers in increasing their approved credit.

B. Main Regression Specification

The predictions of proposition I can be tested empirically since signals $\widehat{H}$ and $\widehat{S}$ are observable to the econometrician as well as the ultimate decision maker. For example, if a firm has subjective information grade of "A" in its credit folder, the loan officer who evaluated the firm will put a higher weight on this "A" compared to a manager looking at the same file.

The only remaining complication in testing proposition 1 is that quality $\widehat{Q}$ is not observable. However, as long as approved credit $L(Q)$ is monotonic in Q, and is observable, sensitivity of Q to information can be translated into credit sensitivity of L to the same information. Let i index a loan applicant firm, and j the loan officer collecting all the information for this firm. Then we can test proposition 1 by estimating an equation of the form:

$$L_{ij} = \alpha + \beta_H * H_{ij} + \beta_H^M * (H_{ij} * MGR_i) + \beta_S * S_{ij} + \beta_S^M * (S_{ij} * MGR_{ij}) + \varepsilon_{ij} \tag{3}$$

where L_{ij} is log of approved credit limit for the loan applicant and MGR_i is an indicator variable for whether loan applicant i is approved by the manager. The main prediction is that $\beta_H^M > 0$ and $\beta_S^M < 0$. With the inclusion of a constant in (3), we no longer have to convert variables into deviations from their means. It is useful to keep in mind that the theory has no prediction on the level of sensitivity to subjective and objective information (i.e. coefficients β_H and β_S in (3)).

We have derived the primary empirical specification (equation (3)) from the theoretical predictions highlighted in the beginning of this section. There are of course practical concerns of identification and normalization of variables in estimating (3). We shall discuss these issues in detail in section III.

II Data Description

We estimate equation (3) using data from a bank whose organizational structure closely mirrors the description in section I. The data covers information contained in the credit folders of all of the 424 corporate clients of a large multinational bank in Argentina in 1998. A firm is classified as corporate by the bank if its annual net sales exceed $50 million pesos[4] The advantage of having full access to these credit folders is that we observe the entire life cycle of loan origination. In particular, our data set contains all of the information collected by a loan officer as part of the loan review process. We also observe the hierarchical level at which a given loan is approved, as well as the approved loan amount.

The timing of a typical loan review at the bank is as follows. Once a firm requests credit from the bank, it is assigned a loan officer who is in charge of developing the firm-bank relationship. At the same time given the basic verifiable information provided by the firm in its application, the bank's credit policy manuals determine the ultimate hierarchical level of approval. Two points are important to emphasize here. First, the final hierarchical level of approval is determined *before* the loan officer collects his firm-specific information. This ex-ante knowledge of who has the final discretion over the approval process is likely to effect incentives of the loan officer collecting information. Second, the final hierarchical level of approval is determined by a set of observable objective firm attributes that do not depend on the loan officer's subjective assessment. These attributes, which we refer to as approval level *rule variables*, are collected as part of the initial loan application (i.e. before the loan officer collects more detailed information in the loan review process). Given these rule variables, a set of pre-specified rules in the credit manual determine which hierarchical level within the bank the loan application must go for final approval.

The pre-specified set of rules in the credit manual guarantee that the loan officer has no discretion in determining the final level of credit approval for a firm. This is rational for a profit maximizing bank. If the bank believes that the loan officer does not have sufficient capability to approve loan for certain firms then it would not want the loan officer to decide what those firms are[5]. There are 5

[4] In 1998 the bank was ranked 3rd in terms of total assets and 5th in terms of net worth among all financial institutions in Argentina. We have signed a non-disclosure agreement with the institution and therefore cannot mention in any written document the name of the institution where the data comes from. During the year 1998 $1 Argentine Peso was equivalent to 1 US Dollar.

[5] There might still be some room for the loan officer to indirectly manipulate how firms are assigned to different levels

different levels of approval in the hierarchical design of our bank, with the loan officer sitting at the lowest level (see Figure II).

Once the final level of credit approval is determined, a loan officer collects detailed information regarding the firm's financials as well as subjective information through interviews and plant visits. The content, type and quality of information is consistent across credit folders, with all credit folders containing the same type of information. Bank credit manuals specify exactly what kind of questions and information each loan officer must seek for a given loan application.

After a loan officer has completed the information required for a given loan application, the application travels sequentially through all hierarchical levels until it reaches its final level of credit approval. The final level of approval can of course be the loan officer himself.

We chose 1998 as the year of our analysis for a couple of reasons. First, as explored in Liberti (2004) the bank went through an important change in its hierarchical structure as well as in the definition of the credit roles of certain account officers in 2000. Using 1998 as the year of analysis will not interfere with any change in the organization or with any potential "leakage" about the change in structure. Second, 1998 was a normal year for Argentina in terms of macro-economic activity and before the large scale economic disruption of December, 2001.

We divide variables constructed from the credit folders into *rule variables* collected at the time of initial loan application, *informational variables* collected by the loan officer as part of the loan review process, and *credit approval variables* determined by the final approving authority. These variables are described in detail below.

A. Approval Level Rule Variables

Given the five hierarchical levels in the bank, Table I shows how firms are distributed across these levels for credit approval. 26.6% of loans[6] are approved at level 1 by the loan officer himself. Another 37.4% are approved at level 2, and the remaining are approximately equally divided among levels 3, 4 and 5.

Firms are sent to one of the five hierarchical levels as determined by the rule variables. Although theoretically there are up to 19 rule variables, many of these are "exceptions" that are used very rarely. In particular there are 11 such variables which *taken together* influence the approval level of

of hierarchy. We shall discuss these issues in greater detail in the next section.

[6] A loan is aggregated at the firm level.

only 48 firms in sample[7]. For brevity we do not report their summary statistics, although they will be included in the regression analysis later on.

The 8 primary variables responsible for assigning applicants to different approval levels are described in Appendix A, and their summary statistics are given in Table I. These variables include applicant characteristics such as loan maturity, applicant size, credit score, industry etc. Table II summarizes the relative importance of different rule variables in determining the final approval level and sheds light on the assignment mechanism used by the bank. It should be kept in mind that credit manual guidelines that map rule variables to approval levels cannot be expressed in a single closed form function. There are a number of discontinuities and trigger points built into the credit manual guidelines. For example, larger applicants are more likely to be sent to higher levels for approval. However this relationship is not smooth, and by necessity there are cutoff points deciding the level of firms. Similarly a number of other reasons, such as maturity structure, firm industry, and credit score can send a firm to higher levels for approval even if the firm falls in a lower level according to applicant size. It is thus a combination of several non-linear rules that decides the ultimate approval level for a firm.

General principles underlying assignment rules can be understood from Table II. It provides means of all rule variables broken down by the five approval levels. The means shows that firms requesting larger loans are more likely to be sent to higher levels for approval. Since bigger firms have larger and more complex funding requirements, the bank is more inclined to send such firms to officers higher up in the hierarchy as they have more experience and expertise. Similarly, firms belonging to volatile industries, poor credit history, long term loans and unsecured loan applications are more likely to be sent to higher levels for approval. On the other hand firms with guarantees from foreign affiliates of the bank are unlikely to be sent up for approval. These patterns again reflect the belief that more senior officers are better able to evaluate more complex loans.

Table III formally investigates the relationship between approval level and rule variables used by the bank's manual to allocate firms across levels. Column (1) includes all of the rule variables on the right hand side, and reaffirms that larger applicants, applicants with worse credit scores, firms with more complex loan requests and firms belonging to volatile or nascent industries are more likely to

[7] These variables are: Requested Amount Exceeding Limits Implied by Firm Size, Downgrade in Firm Capital Structure Score, Risk Event At The Company, Adverse Change In Risk Profile, Adverse Change In Critical Success Factors, Covenant Violations, Qualified Auditors and Override In Debt Rating Model.

be sent to higher levels for approval. These results are very much in line with the "management by exception" criteria of Garicano (2000), where the role of a hierarchy is to conserve the time of experts so that they only intervene when no one else can solve a problem. Although column (1) includes all of the rule variables used by the bank, the R-sq is still only 0.44. The low R-sq reflects the non-linear nature of the assignment procedure followed by the bank. It is neither due to the bank ignoring assignment rules at times, nor is it due to missing rule variables. For example, we can get an "R-sq" of 1 if we manually apply the credit manual procedure to the rule variables associated with each firm. The "predicted" approval level from doing this exercise matches the actual approval level is all of the 424 firms in our sample.

Column (2) includes all pair-wise interactions of the top 4 rule variables to allow for some non-linearities. The R-sq remains very similar. Column (3) adds higher powers of the rule variables by including functions of powers 2 and 3 for the rule variables. The R-sq increases slightly to 0.5 as a result. Furthermore most of the variation in approval levels in the simple OLS regressions is explained by the top 4 rule variables in terms of significance. Column (4) shows that these top 4 variables account for almost all of the explained variation in column (1) (R-sq is 0.35 vs. 0.44 in column (1)).

Since approval levels only take integer values, OLS may not be an appropriate estimation technique. Correspondingly we experiment with ordered probit and ordered logit specification in columns (5) and (6). However, even with such non-normal estimation techniques pseudo R-sq is not very high.

B. Informational Variables

Once a credit application is filed and its ultimate approval level is known, the credit folder is given to a loan officer (LO) who collects all the firm level information. A typical loan officer manages around 20-25 firms (on average) that are mostly clustered in a single or related industries[8]. The collected information includes objective information from audited firm financials, as well as subjective assessment of firm quality by the loan officer. The subjective assessment is based upon visits to firm premises and interviews with firm management.

Our data set includes all of the objective and subjective pieces of information collected by the loan officer as per bank rules. The bank pre-specifies what pieces of information have to be collected by a loan officer. In order to avoid concerns of "data mining", we desist from picking and choosing

[8] For a description of the selection of firms into loan officers see Liberti (2004).

any particular set of informational variables. Instead in the analysis that follows, we use *all* of the informational variables collected by a loan officer. These variables are naturally classified by the bank into two categories.

The first category of variables measure some cardinal firm characteristic. This category includes firm financials from audited records, and we classify it as *objective* information. Appendix B provides the full list of objective variables, which include leverage ratios, profitability, and size. We classify these variables as objective since they are quantifiable, easy to collect and transmit, and are verified by a third party (the auditor). Therefore a loan officer collecting this information does not have any discretion in how to report it, and also does not need much effort or expertise in collecting such information.

Since the objective variables (in particular leverage ratios) can have large variance, the bank translates these ratios according to a pre-specified formula into a rating that goes from 0 to 22 for all financial ratios, and 1 to 6 for firm size. The ratings are a monotonic categorization of the financial ratios. The bank also constructs an overall index of these financial ratios and size information that we define as *objective index.* We standardize this index by subtracting the sample mean and dividing by the sample standard deviation. We also divide objective index into two (standardized) sub-indices: a *performance index* that averages all of the leverage, profitability and current financial ratios, and a *size index* composed of firm size.

The second category of informational variables collected by the bank are subjective ordinal rankings provided by the loan officer. These variables, which we classify as *subjective* information, are personal assessments of the loan officer on various firm and management attributes. A differentiating feature of subjective information is that it involves discretion on part of the loan officer, and requires him to invest effort and expertise in order to collect reliable information. As with objective information, the bank pre-specifies what pieces of subjective information a loan officer must collect. These variables are described in Appendix C, and include loan officer's assessment of management quality, accounting practices, firm's risk management policies, firm's overall market positioning, industry outlook and firm's access to external capital markets. The loan officer assigns an ordinal (subjective) score of 1 through 7 to each subjective firm attribute, with larger scores signifying higher firm quality. For any given subjective variables, a particular score corresponds to a pre-defined criteria. For example, a 3 in professionalism corresponds to "at some key positions", while a 5 corresponds to "at all key positions in operations and management". Appendix D provides a mapping of subjective categories into their respective definitions for all variables.

The bank also aggregates its subjective information into an overall index, which is standardized to provide us our *subjective index*. Although all variables that are reported as ordinal rankings are initially combined into one subjective index, they differ in the degree of their subjectivity. For example, when a loan officer is asked to report on a firm's ability to access outside funds, he may use some objective verifiable information such as existing firm lenders to arrive at an answer. However, a question regarding a firm's "professionalism" is considerably more subjective. We therefore also construct two sub-indices of the overall subjective index into a *strong subjective index* and a *weak subjective index*. The strong subjective index is a standardized average of management and competitive position variables which we think involve more subjectivity, a priori, than other variables. Variables in industry risk assessment, risk management policies, and access to capital categories on the other hand are classified as weakly subjective since they are partially based on objective information such as lending by other banks, or industry sales trends etc.

Table I provides a summary of the information indices and sub-indices. Although we stick with the bank's construction of objective and subjective indices (to avoid concerns of data mining), our results are completely robust to alternative definitions of objective and subjective indices as we shall discuss in the robustness section. Table IV provides the correlation matrix for the various sub-components of subjective and objective indices. The sub-components are positively correlated as expected. However the correlation is not perfect signifying the independent component that each sub-component brings to the overall indices. We shall explore the variation in sub-components in some of the analysis as well.

C. Credit Approval Variables

Once a loan officer collects all required information, credit is approved and authorized by the loan officer himself if he has the authority to do so. Else the credit file is sent up the hierarchy towards the bank officer with the approving authority. The average credit facility provided by the bank in 1998 was 16.6 million dollars and there is significant variation in this amount across firms (Table I). The approved credit line aggregates all short, medium and long term financing provided by the bank. Once a credit line is approved, a firm does not have to utilize all of it. In fact the average outstanding loan for a given firm is 10.7 million dollars. The difference between approved and outstanding amounts partly reflects liquidity management on part of firms as their short term credit demand fluctuates.

Other variables collected by the bank include credit risk rating of the firm, an indicator as to whether the firm is in financial distress, maturity of all existing facilities over 3 years, % of unsecured existing facilities, legal history of default and covenant violations, years in industry, ownership type and access to other financial institutions. We also have some specific information such as the time (in days) taken by the credit analyst and LO to prepare the credit recommendation form and whether additional information was requested by the loan officer along the process. Our final data set includes all clients with approved credit lines in 1998. However, if a credit application were rejected by the bank, we do not have it in our data.

III Empirical Methodology

A. Identification

We can estimate equation (3) using data described above since the data contains subjective and objective risk rating indices (S and H) collected by the loan officer, variation in the hierarchical level of approval, as well as the final approved loan amount. However, proper identification of coefficients β_H^M and β_S^M requires that the estimated coefficients are only influenced by the direct effect of hierarchical level of approval and not by spurious omitted variables. The fundamental identification concern is the endogenous assignment of firms to different hierarchical levels and endogenous assignment of loan officers to different firms. We describe these endogenous assignment concerns below, and also our methodology for addressing each concern.

(i) Endogenous Bank Assignment

Identification of equation (3) works best if the bank allocates firms to different credit approval levels at random. However, as we have already indicated, the bank has a well-specified mechanism that assigns firms to various approval levels based on certain firm characteristics (i.e. the *rule variables*). The concern therefore is that firms sent to higher levels for approval are inherently different in terms of how important objective and subjective information is in evaluating them. For example, suppose that firms with less reliable subjective information are deliberately sent further up in the hierarchy because more senior bank officers are better able to tackle complicated loans with poor subjective information. In such a scenario even if there is no loss of subjective information across hierarchies, managers will put less weight on subjective information compared to loan officers since their firms have poorer quality subjective information to begin with. Alternatively if firms with better objective information such as large firms with well audited financials and long track records are sent higher up the hierarchy, then managers will put more weight on objective relative to subjective information even if there is no loss of informativeness in communicating subjective information.

More formally let Z be a firm characteristic that the bank uses to assign firms to higher levels of approval. For simplicity assume that there is only one such variable, say size. The bank chooses a cutoff size $\overline{Z}$ such that firms above this threshold are sent to the manager for approval while others are sent to the loan officer. Figure III shows the function mapping Z to approval level. The endogeneity concern is that larger firms might have less relevant subjective information, i.e. σ^2_{qs} is lower for larger firms for any given level of effort put in by a loan officer. If this were the case then β^M_S would be biased downwards and one might get a significant and negative coefficient even if subjective information were communicated to the manager without any loss of informativeness.

Let $\overline{\sigma^2_{qh}}$ and $\overline{\sigma^2_{qs}}$ denote the maximum possible informativeness of objective and subjective information for a firm, i.e. the informativeness that the best loan officer can generate if he works efficiently. Then the general concern is that any bank assignment criteria Z might be positively correlated with $\overline{\sigma^2_{qh}}$ and/or negatively correlated with $\overline{\sigma^2_{qs}}$. Figure III plots some possible relationships between Z and $\overline{\sigma^2_{qs}}$, and Z and $\overline{\sigma^2_{qh}}$ that can bias β^M_S downwards and β^M_H upwards respectively.

The endogenous bank assignment concern highlighted in figure III is almost impossible to address if Z is unknown or not observable. However, as pointed out, the bank has a pre-specified list of rule variables (i.e. $Z's$) that determine which level a firm gets sent to. Moreover these rule variables are based on third party objective criteria and not subject to the loan officer's discretion. We can therefore control for endogenous bank assignment concerns by including Z, $(Z * S)$ and $(Z * H)$ as controls in (3). We can also include higher powers of Z (such as Z^2) and their interactions with H and S to allow for greater functional form flexibility.

The inclusion of linear and quadratic bank selection controls implies that the identification of β^M_H and β^M_S is coming from the non-linear and discontinuous part of the relationship between rule variables Z and approval levels. For example, by necessity approval levels have to be partly a non-linear and discontinuous function of the ex-ante firm selection variables. Once we control for linear and quadratic components of Z, it is these non-linearities and "jumps" in the residual variance that are used to identify β_H^M and β_S^M.

(ii) Endogenous Self-Assignment

Even though assignment of firms to different hierarchical levels is based on pre-specified firm characteristics and not on loan officer's discretion, it is still possible that firms at the margin can manipulate their attributes enough to fall into a more preferable approval level. For example, suppose a firm knows the approval level assignment mechanism of the bank. Then the firm might want to manipulate the level assignment process to get assigned to its desired level of approval. However endogenous self-assignment is only a concern if firms with inherently better quality subjective information self select to lower levels. Such selection might happen if firms with better quality subjective information *know* that lower level officers are better at using subjective information. Thus for endogenous self-assignment to exist, hierarchies must have an effect on information use in the first place. In other words, endogenous self-assignment might overstate an existing effect, but it is hard to generate an effect if none exists.

There is a natural way to test if firm self selection is overstating the true effect of hierarchies in our sample. The insight comes from the observation that manipulating ones attributes is likely to be costly for a firm. For example, if a firm wants to request for a 2 million peso loan but requests only 1 million so as to go to a lower level, then this deviation from true demand is likely to hurt the firm. Therefore if firms manipulate their true information in order to get assigned to a lower (or higher) approval level, they would manipulate information only as much as necessary. Correspondingly firms subject to self selection will lie on the margin between two different approval levels.

Therefore a simple way to control for firm self selection is to drop firms that are on the boundary between two different approval levels. After dropping such firms that are on the margin between high and low levels, the remaining firms are unlikely to suffer from self selection concerns.

(iii) Endogenous Loan Officer Assignment

A separate concern in estimating (3) is the endogenous assignment of loan officers to firms. Since information for all types of firms is collected by the loan officers, it might be the case that firms approved by loan officers themselves are given to loan officers with better ability and expertise in collecting subjective information. If this were the case then firms approved by loan officers will get higher weight on subjective information not because of the lower level of approval, but because the loan officer was better at collecting subjective information.

Since we know the identity of the loan officer collecting information for each firm, we can fully address the loan officer selection concern by including loan officer fixed effects, and interacting these fixed effects with H and S. This non-parametric approach ensures that we only compare firms at different approval levels whose information was collected by the *same* loan officer. Bank selection controls and loan fixed effects (α_i) update (3) to:

$$L_{ij} = \alpha_j + (\alpha_j * H_{ij}) + (\alpha_j * S_{ij}) + \beta_H^M * (H_{ij} * MGR_i) + \beta_S^M * (S_{ij} * MGR_{ij}) + \beta_1 Z_i + \beta_2 (H_{ij} * Z_i) + \beta_3 (S_{ij} * Z_i) + \varepsilon_{ij} \tag{4}$$

B. Other Issues

The statistical framework outlined in section I, and the resulting estimation equation III were based on one period model of the loan approval process. In reality, there will be repeated loan applicants as well. However, in principle, this should not affect either the updating equation (2) and hence our primary estimation equation. Even with repeated interaction, state of economy, industry outlook, and nature of firms is continuously changing. Hence there is a continuous need for updating information and accommodating credit limits in response. Nonetheless, we have information on whether a firm has had prior relationship with the bank, and if so for how long. Therefore, we can explicitly test for whether the length of relationship affects the sensitivity of lending to information. There may also be a concern of conditioning approved loan amount on firm size or latent firm loan demand. For this reason, we shall condition all of our results on firm size, by putting firm size on the right hand side as well.

IV Results

A. Effect of Hierarchy on Information Use

The main regression specification (3) can be tested using the methodology and data described earlier. We begin by collapsing the 5 approval levels into “high” and “low” around the median. This classifies approval levels 1 and 2 as "low", and levels 3, 4 and 5 as "high". Column (1) of Table V estimates equation (3) using log of approved credit line as the dependent variable. Coefficients on interaction between information indices and high level dummy show that sensitivity of credit approval to subjective information dramatically goes down for loans approved higher up in the hierarchy, while sensitivity to objective information increases for loans approved at high level.

These results are consistent with theoretical prediction highlighted in proposition 1. However as section III explained, the result may also be driven by endogenous assignment of firms and/or loan officers. Column (2) includes loan officer fixed effects and their interactions with objective and subjective indices. There are a total of 26 loan officers. The fixed effects non-parametrically control for the person generating subjective and objective information, and force comparison between firms whose objective and subjective information is generated by the *same* loan officer. The results are very similar to those of column (1).

Column (3) then controls for endogenous bank assignment concern by including variables used by the bank to assign firms to different levels as controls. We include these rule variables and their interactions with objective and subjective information indices as controls as well (i.e. we estimate equation (4)). As we explained in methodology section, the linear controls and their interactions imply that identification is only coming from the non-linearities inherent in the bank assignment process. Column (4) further supplements these controls by incorporating quadratic powers of rule variables and their interactions with information indices as controls. The results indicate that our main coefficients of interest remain qualitatively unchanged. It is worth emphasizing that the amount of loan requested by an applicant is one of the controls in columns (3) and (4). In other words, RHS and LHS variables are conditioned on the amount of loan requested by an applicant.

Since we are exploiting non-linearities in rule approval to identify our coefficient of interest in column (3), the increase in objective information sensitivity and decrease in subjective information sensitivity at higher levels is unlikely to be driven by spurious bank assignment criteria. The magnitude of the effect of hierarchical distance is large. Since all informational variables have already been normalized, the coefficients can be interpreted as the effect of a one standard deviation change in information variables. Columns (1) through (4) thus highlight the large swings in sensitivity as a result of hierarchical distance. It might appear odd at first that the coefficient on objective information is essentially zero at low level of approval and that the coefficient on subjective information is almost zero at high level of approval (column (1)). However, this does not literally mean that objective information is worthless at low approval level. If we take out subjective information from column (1), then objective information is positive at low levels as well. In other words, it is the component of objective information that is orthogonal to subjective information that is not given any weight in the credit making decision by officers at low levels.

Table V had collapsed the 5 hierarchical levels into two. Columns (1), (2) and (3) in Table VI open up these 5 levels to see how sensitivity to information changes at each level. Column (2) includes loan officer fixed effects and their interactions with information indices, while column (3) adds bank selection criteria variables and their interactions with information indices as well. The results show that the change in credit sensitivity is not gradual across the 5 approval levels. The change in sensitivity to subjective and objective information happens relatively *sharply* at level 3 and then persists at higher approval levels. Furthermore, as before results are symmetric for subjective and objective information. Sensitivity to subjective information declines at level 3 and beyond, while sensitivity to objective information increases at the same levels.

Results in columns (1) through (3) also suggest a way to control for the remaining endogeneity concern, *i.e.* applicant self-assignment. As discussed in the methodology section, self-assignment might be an issue for applicants that lie on the margin between high and low approval levels. A firm will only manipulate information if such manipulation puts it in a level more conducive to the type of information the firm has a comparative advantage in. Since our effect kicks in when a firm goes from level 2 to level 3, all marginal firms are going to be either in level 2 or level 3. This suggests that one can control for endogenous self-assignment by dropping firms belonging to level 2 and 3. While column (1) through (3) already indicate that our results should hold even after removing level 2 and 3 applicants, column (4) confirms this by running the primary regression specification (3) on 212 firms belonging to levels 1, 4 and 5. Level 1 firms are classified as "low" and firms belonging to levels 4 and 5 classified as "high". The results confirm that endogenous self-assignment is an unlikely explanation of our main result.

In summary Tables V and VI suggest that endogenous firm assignment to hierarchical levels ,whether driven from the bank side or by firms themselves is unlikely to explain our results. Similarly loan officer fixed effects show that endogenous assignment of loan officers cannot explain our results either. We can thus be more confident in the interpretation that sending a firm higher up for approval decreases reliance on subjective information, and increases reliance on objective information.

B. Does Geographical Location Matter For Information Flow?

If changes in information sensitivity are truly driven by the level of approval, then why does the effect kick in at level 3? For example, why is the effect not more gradual from level 1 through level 5? If the information sensitivity effect is coming from differences in organizational structure of the loan approval process, then how are approvals at level 2 so much different from approval at level 3, but not from approval at level 1?

The geographical location of officers at different hierarchical levels presents a possible explanation. Our data includes information on the location of each officer involved in the loan process. Panel A of Table VII shows the joint distribution of the level of approval, and geographical distance between a loan officer and the officer approving a given loan. The variable, geographical distance, is defined as 0 is the loan officer who collects information and the loan approving officer sit in the same branch. Otherwise it is coded as 1. The joint distribution shows that loan officers collecting information and loan approval officers at level 2 *always* sit in the same bank branch. They can therefore interact and communicate on a daily basis with ease and are likely to know each other quite well. Since there is equal sensitivity to objective and subjective information among level 1 and level 2 approvals, it suggests that communicating subjective information among co-workers who work in close geographical proximity is easy.

Officers above level 2 on the other hand do not always sit in the same bank branch as the loan officer. In fact level 4 and 5 officers *never* sit in the same branch as their loan officers. These officers sit in the larger headquarter offices and sometimes even outside the country. Officers at level 3 however sometimes sit inside and sometimes outside the local branch where information is collected. Out of 54 firms that are approved by officers at level 3, 17 are approved by officers who sit at the same branch and 37 by officers who sit at a different location.

We exploit variation in location of the loan approving officer to formally test whether results in Table V were driven by the loss in informativeness due to officers sitting at different geographical locations. Column (1) of Table VII, Panel B run the primary regressions but replace hierarchical distance with geographical distance. The results show that the change in sensitivity to information happens when the approving officer sits in a different geographical location than the loan officer collecting information. However, as Panel A showed, geographical and hierarchical distance are highly correlated. The only independent variation in geographical distance occurs for loans approved at level 3. Therefore, column (2) repeats the test of column (1), but this time restricts sample to the set of 54 firms that are approved at level 3. Even though the number of observations is much smaller, coefficients on interaction terms support the hypothesis that differences in geographical location are an important factor in the loss of informativeness. When a level 3 officer sits in the same branch as the loan officer, his sensitivity to subjective information is much higher than a level 3 officer that sits outside the loan officer's branch. Similarly, sensitivity to objective information increases when the officer sits outside the branch of the loan officer[9]. Column (3) repeats column (2) on the full data, but includes all the approval level dummies and their interactions with informational indices. It thus replicates column (2), but is more efficient for computing standard errors. The results are almost identical.

The fact that changes in sensitivity to information are not gradual, but happen suddenly in between levels where the geographical location of approving officers is different from loan officers, further strengthens the interpretation that differential sensitivity is driven by organizational differences in the loan approval process of different firms.

C. Are More Experienced Loan Officers Better At Communicating Subjective Information?

The usefulness of co-location for communicating subjective information suggests the importance of repeated interactions. Geographical proximity facilitates repeated interactions which help in understanding and relying on each other's subjective information. While geographical proximity is useful, a substitute for proximity might be repeated interactions over time. For example a more experienced loan officer is likely to have interacted with senior officers more often which can make the interpretation of subjective information easier for high level officers. An analogy may be drawn here with the academic job market where a recruitment committee might give more weight to a recommendation if they have personally interacted with the recommending professor often over time.

Since we have information on the experience of a loan officer within the bank, we can test whether

[9] We also compared basic descriptive statistics for level 3 firms approved inside and outside the loan officer's branch. The firms are in general quite similar, showing that the geographical location of level 3 officers is not systematically biased in a particular direction so as to bias our coefficients of interest. Also note that since we are only using variation from 54 observations to identify our coefficient of interest, we no longer have the power to put in our usual set of control variables.

this experience facilitates subjective information communication. We do so through our loan officer fixed effects specification and add triple interactions of subjective and objective information sensitivities with loan officers' experience. The results in columns (1) and (2) of table VIII show that the decline in subjective information sensitivity is much smaller for more experienced loan officers.

Since we use loan officers' fixed effects and their interactions with objective and subjective variables as well, our result cannot be driven by more experienced loan officers having better overall quality of subjective information. A higher overall level of subjective information can explain an overall greater sensitivity to subjective information for all bank officers, but it cannot explain why the sensitivity improves more for higher level officers. Thus experience of a loan officer likely improves the communication of subjective information across hierarchies.

D. Is The Effect Stronger For More Subjective Information?

So far we have used the objective and subjective indices constructed by the bank to measure credit sensitivity. However, since we also have the underlying variables used to construct these indices, we can check for robustness of results to different ways of aggregating the underlying variables. We first explore variation in subjective information variables. Appendix B provided details of all the subjective information variables used to construct subjective information rating. There are a total of 18 primary subjective information variables, divided across five subjective information categories. The bank uses its own formula to weight these 18 variables in coming up with an overall subjective ranking. While we are not at liberty to disclose the bank's internal rating construction, we can construct alternative indices of our own using these 18 variables.

We construct two different definitions of overall subjective information rank. (i) AVGsubjective: This is a simple arithmetic mean of all the 18 subjective information variables, and (ii) WAVGsubjective: This weighs the five categories equally while giving equal weights to the subjective information variables within each category. Columns (1) and (2) in Table IX repeat the primary regression specification but replace subjective information rating with AVGsubjective and WAVGsubjective respectively. The result on credit sensitivity to subjective information are very similar in spirit to what we found earlier. As such our main result is not sensitive to the definition of how subjective information index is constructed.

Subjective information variables also differ in their "subjectiveness" or the extent of subjectivity involved in computing them. If sensitivity to subjective information declines as a result of communication losses across hierarchies then one would expect such losses to be greater for more subjective variables. We therefore divide subjective variables according to the degree of subjectivity involved in computing them and split the subjective index into a strong subjective index, and a weak subjective index (section II explained their construction).

Columns (3) through (5) test whether the drop in sensitivity to subjective information as higher levels is stronger for more subjective information. The results indicate that the drop in sensitivity of subjective information is stronger for the more subjective sub-index. This result is also in-line with our earlier results and interpretation that it is the subjectivity of information that makes it difficult to communicate across hierarchies. For example, consider the components of the weak subjective index. In coming up with industry outlook indices a loan officer may use publicly verifiable industry data such as recent growth and volatility. Rating a firm's leverage or liquidity policy can also be judged to a reasonable extent from its balance sheet numbers. Similarly access to capital data is generally available in verifiable formats such as central credit registry data or knowing the number of relationships the firm has access to.

On the other hand, components of the strong subjective index such as, variables linked to a firm's competitiveness and management quality are more subjective. For instance, ranking a firm's "professionalism", "ability to act decisively", or "technology advantage" is inherently a much more subjective exercise.

Finally we test for the robustness of our results to the definition of objective information index. As explained earlier, the bank uses seven different financial ratios to arrive at its objective information rating that we have so far used in our analysis. We also constructed our own index of objective information by taking the arithmetic mean of these financial ratios. Results with our index of objective information are qualitatively very similar to those obtained with the bank's objective risk rating (regressions not shown).

V Discussion of Results

Our results indicate that greater hierarchical distance makes it difficult to use subjective information and favors the use of objective information instead. A number of tests, such as exploring non-linearities in assignment of applicants to approval levels and loan officer fixed effects, showed that the results are not driven by spurious correlations. Further results on the importance of co-location of loan officer and loan approving officer, and experience of the loan officer bolster the importance of organizational design on information use.

Section I explained that a number of different theories all suggest that hierarchical distance should favor objective over subjective information. Given that our results confirm this common prediction, we now outline which economic interpretation is more favorable in the light of our results.

A. Loss in Communication

One interpretation of our results is based on theories of costly communication. In particular, subjective information may be more costly to communicate across hierarchies particularly when communicating parties are geographically separated, and when the person generating information has been with the bank for a brief period of time. Subjective information is harder to communicate between people who do not work together since they are not fully aware of each others trust, competence, and judgement criteria. For example, it is easier for coauthors to exchange (subjective) ideas if they work in the same building compared to coauthors working in separate cities. This interpretation is consistent with our result that credit sensitivity to subjective information declines at higher levels, that the decline is larger for more subjective information that the drop in sensitivity only kicks in when an officer in the higher hierarchy is located in a different branch, and the effect is strongest.

B. Incentives to Gather Information

A slightly different interpretation of our results could be that when a loan officer has little control over the use of his information, he has less incentives to gather quality information. The view that decision making authority increases a loan officer's incentives to collect information has already been proposed in papers such as Aghion and Tirole (1997) and Stein (2002). An incentive based explanation is more likely to effect subjective information acquisition since this type of information requires more effort and thinking on part of the loan officer. For an incentive based story to explain all of our results, we need to assume that the loss of incentives is not great when the person making the final credit decision works in close geographical proximity of the loan officer. In other words the loan officer must feel sufficiently part of the decision making process if the approving officer work close to him. Similarly we have to assume that greater subjectivity of a variables increases the effort required from a loan officer. In such a case more subjective information is more likely to be affected by an incentive effect.

C. Strategic Manipulation of Information

A loan officer might strategically manipulate and coarsify his information, as in Crawford and Sobel (1982), if he does not have control over decision making. For example, this might be done in an effort to retain more control by the loan officers themselves, or to make the decisions of other officers look worse. Since objective information is more difficult to manipulate, loan officers are more likely to manipulate subjective information. Therefore if strategic manipulation exists in equilibrium, officers at higher approval levels will deliberately put less weight on subjective information as they know the information has been tempered with.

However we feel that strategic manipulation is unlikely to be a main explanation of our results. Loan officers must also have an incentive to provide accurate and useful information to their superiors in order to maximize their chances of promotion and career development. Such incentives should suppress the desires to manipulate information. Similarly the effect of strategic manipulation should have been seen when level 2 officer has discretion over credit approval. However the drop in sensitivity to subjective information is only seen at level 3 and beyond, and only when the decision making officer sits in a separate branch. This evidence also lowers the likelihood of strategic manipulation as a primary explanation of our results.

D. Different Abilities or Objectives

Officers at different levels may have different abilities to handle objective and subjective information variables. Alternatively officers at different levels may have different tastes or objectives in terms of incorporating objective and subjective information into their decisions. However, there is no particular theory to suggest why such differences might exist. The bank also has identical lending guidelines for loan approval regardless of the hierarchical level of approval.

Even if differences in objectives exist, there is no strong reason to suggest that officers at higher levels should have a stronger bias against subjective information. Moreover any theory based on differences in tastes and abilities will have to argue that such differences do not exist between levels 1 and 2, but do exist at higher levels, and only kick in when officers at higher levels are sitting in a different branch. As such it is difficult to come up with a plausible explanation for our results based on differences in objectives alone.

E. Corruption or Related Lending

Since approvals at lower levels of hierarchy rely more on subjective information, perhaps the evidence reflects corruption or related lending by local branches. Corrupt lending refers to loans that are not based on any informational advantage, but rather loans that do not deserve to be made on financial grounds. However, corruption is unlikely to be an explanation for our results. First, the bank we study is a multinational bank with assets all over the world. With so much reputational capital at stake, the bank is very unlikely to engage in related lending in a small market. Even less likely is the scenario that the bank would only engage in such related lending at lower levels of hierarchy and not at higher levels. Second, we have ownership information on borrowers. None of the borrowing firms are "related" to loan officers, or loan approving officers inside the bank.

VI Concluding Remarks

Our main purpose was to test how hierarchical design impacts information sharing and use. Does the impact of hierarchical distance on information sharing also effect the efficiency of financial intermediation? While it is an important question, we are limited in how far we can answer it. Measuring efficiency of financial intermediation is difficult since measures such as default and firm profitability can be misleading. For example, realized default can be a very poor proxy for expected default, particularly in volatile and non-stationary environments like Argentina. This is especially problematic for us since Argentina went through a massive economic crisis a couple of year after our sample period in 2001. Nonetheless, using outcome measure such as future firm default, and future firm profitability, we find no systematic difference between applicants getting approvals at high versus low hierarchical levels.

We should also point out that our analysis took the hierarchical design in our sample as given. As such questions regarding whether the hierarchical design is optimal remain outside the scope of our paper. Optimal organizational design involves not just concerns of information sharing, but also a host of other issues such as career concerns, task specialization, etc. A meaningful analysis of organizational optmality needs to take all of these dimensions into account.

A lot has been written on how the design of organizations affects incentives, flow of information, and ultimately the scope of firms. Yet our empirical understanding of these issues lags far behind. The reasons are mostly obvious. Information at the intra-firm level is seldom collected, and firms are reluctant to share such information. Even with available information, it is difficult to find exogenous variation in the organizational attribute of interest for identification. Furthermore, several theoretical constructs such as “power” and “soft information” are difficult to define empirically. The methodology adopted in this paper aimed to address some of these issues as we had a rare opportunity to peek inside the decision making process of a large hierarchy.

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Figure I:
An Example of Bank Hierarchical Structure

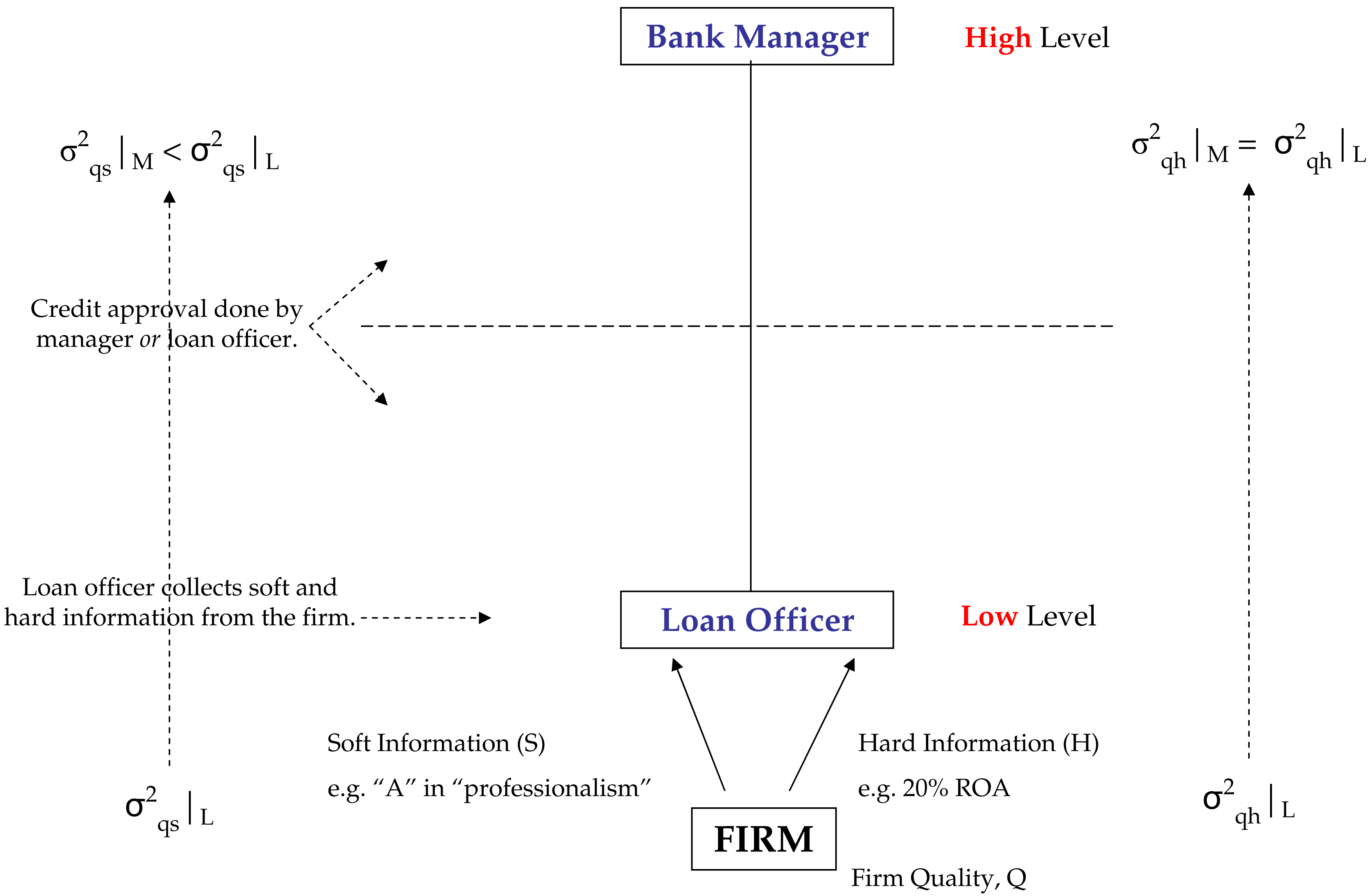

Figure II:
Hierarchical Decision-Making Process

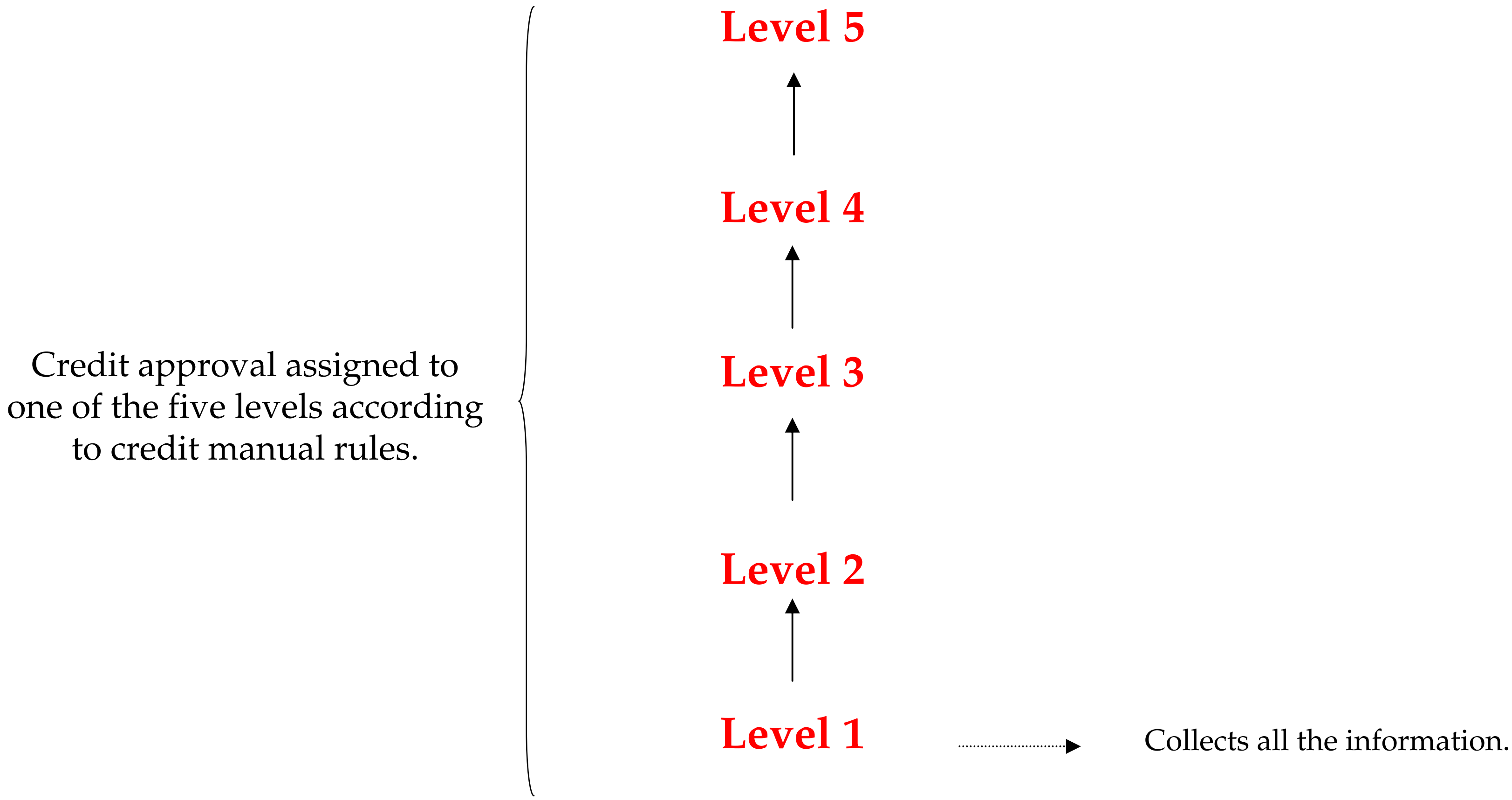

Figure III:
Empirical Strategy

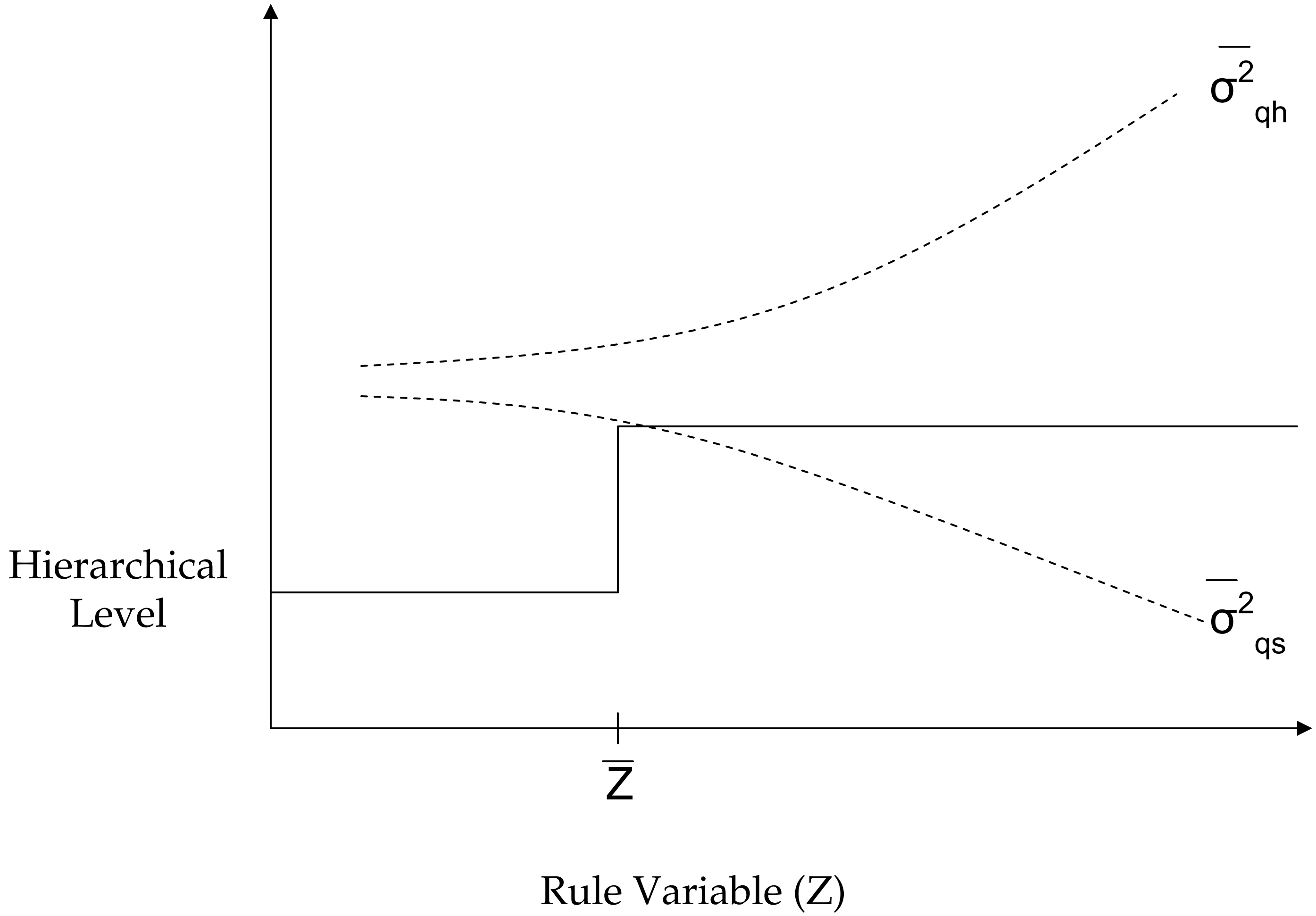

TABLE I
SUMMARY STATISTICS

Variable	Percent of Firms	No. of Firms
Approval Level Indicator Variables		
Level 1	26.6%	114
Level 2	36.8%	158
Level 3	13.1%	56
Level 4	13.5%	58
Level 5	10.0%	43

Variable	Mean	SD	Min.	Max.	Obs.
Approval Level Rule Variables (*)					
Maturity / Collateral Score	12.39	4.15	1.00	22.00	424
Applicant Size (in Million $)	19.86	34.81	0.00	362.00	424
Central Bank Credit Score	1.20	0.58	1.00	4.00	424
Foreign Bank Branch Guarantee	0.23	0.42	0.00	1.00	424
Family Company?	0.16	0.37	0.00	1.00	424
Target Market Industry	0.27	0.45	0.00	1.00	424
Accepted Risk Industry	0.16	0.37	0.00	1.00	424
Declining Industry	0.06	0.23	0.00	1.00	424
Information Indices					
Objective Index	0.00	1.00	-1.82	3.25	424
Performance Index	0.00	1.00	-1.73	2.47	424
Size Index	0.00	1.00	-0.88	2.60	424
Subjective Index	0.00	1.00	-3.75	2.33	424
Strong Subjective Index	0.00	1.00	-3.85	3.58	409
Weak Subjective Index	0.00	1.00	-3.35	3.56	409

*There are nine additional rule variables that correspond to some rare exceptions affecting only 48 firms. These rule variables are not reported as summary statistics for brevity, but they are used as controls whenever other rule variables are included a

TABLE 1 (Continued)
SUMMARY STATISTICS

Variable	Mean	SD	Min.	Max.	Obs.	Median
Other Variables						
Total Facilities (in Million $)	16.68	28.76	0.00	260.88	424	6.00
Total Outstanding (in Million $)	10.79	21.48	0.00	172.53	424	2.66
Net Sales (in Million $)	224.95	516.62	0.00	5500.00	423	66.04
Net Income (in Million $)	9.53	52.60	-157.59	580.00	423	0.63
Total Assets (in Million $)	355.84	1001.01	0.03	13146.00	423	85.93

TABLE II
MEANS OF VARIABLES BY APPROVED LEVELS

	Level 1	Level 2	Level 3	Level 4	Level 5
Number of firms	114	158	56	58	43
Approval Level Rule Variables					
Maturity / Collateral Score	9.61	11.89	14.37	14.43	16.40
Applicant Size (in Million $)	6.53	17.19	17.54	41.42	42.00
Central Bank Credit Score	1.06	1.09	1.24	1.23	1.88
Foreign Bank Branch Guarantee	0.74	0.02	0.01	0.00	0.00
Family Company?	0.06	0.07	0.44	0.25	0.29
Target Market Industry	0.13	0.10	0.50	0.61	0.50
Accepted Risk Industry	0.02	0.05	0.35	0.40	0.33
Declining Industry	0.04	0.02	0.24	0.09	0.00
Information Indices					
Objective Index	-0.36	-0.19	0.39	0.65	0.34
Performance Index	0.038	-0.06	0.38	-0.071	-0.22
Size Index	-0.56	-0.21	0.17	1.01	0.71
Subjective Index	-0.32	-0.094	0.022	0.57	0.41
Strong Subjective Index	-0.32	-0.137	0.126	0.36	0.48
Weak Subjective Index	-0.25	-0.149	0.144	0.40	0.44
Other Variables					
Total Facilities (in Million $)	5.49	16.26	14.30	34.59	26.41
Total Outstanding (in Million $)	3.03	10.21	8.31	22.24	20.94
Net Sales (in Million $)	57.64	140.41	304.90	488.29	545.68
Net Income (in Million $)	0.56	1.12	14.66	14.24	55.50
Net Worth (in Million $)	24.93	57.05	139.98	389.62	590.23
Total Assets (in Million $)	64.83	145.86	293.21	862.43	1333.80

TABLE III
RULE VARIABLES AND LEVEL ASSIGNMENT

This table estimates approval level based on functions of rule variables used in the credit manuals to assign approval levels to firms. Approval level varies from 1 to 5. Regressions include all of the 19 rule variables. However for brevity we only report coefficients on the important ones (see Table I footnote for further details).

Dependent Variable	Approval Level					
	OLS				Ordered Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
Maturity / Collateral Score	0.06	0.12	-0.16	-0.02	-0.05	-0.35
	(0.01)	(0.08)	(0.15)	(0.02)	(0.04)	(0.19)
Applicant Size	0.31	0.47	1.34	0.32	0.40	1.30
	(0.03)	(0.12)	(1.47)	(0.04)	(0.05)	(0.37)
Central Bank Credit Score	0.46	0.75	6.25	0.53	0.54	1.27
	(0.08)	(0.44)	(2.47)	(0.08)	(0.11)	(0.56)
Foreign Bank Branch Guarantee	-1.23	-0.29	-1.24	-1.45	-1.26	-2.39
	(0.11)	(0.45)	(0.11)	(0.11)	(0.29)	(0.30)
Family Company?	0.30	0.32	1.34		0.38	0.36
	(0.13)	(0.14)	(1.47)		(0.18)	(0.18)
Target Market Industry	0.38	0.16	0.37		0.31	0.31
	(0.12)	(0.46)	(0.12)		(0.16)	(0.16)
Accepted Risk Industry	0.48	0.92	0.47		0.54	0.58
	(0.14)	(0.68)	(0.14)		(0.18)	(0.19)
Declining Industry	-0.58	0.79	-0.57		-0.69	-0.69
	(0.20)	(2.05)	(0.19)		(0.25)	(0.25)
Pair-wise Interaction Of Top 4 Rule Variables		Yes	Yes			Yes
Powers 2 and 3 of Rule Variables included?			Yes			Yes
No. of Obs.	424	424	424	424	429	429
Adj R-sq / Pseudo R-sq	0.44	0.44	0.5	0.35	0.19	0.20

TABLE IV
CORRELATION MATRIX OF INFORMATION INDICES AND THEIR SUBCOMPONENTS

PANEL A: Correlation matrix for sub components of objective index

	Pre-tax Interest Coverage	Pre-tax Funds Flow Interest Coverage	Funds from operations/ Total Debt	Free Oper Cash Flow/Total Debt	Pre-Tax Return on Avg Capital	Total Debt / Capitaliza tion	Current Ratio	Size
Pre-tax Interest Coverage	1.00							
Pre-tax Funds Flow Interest Cover	0.91	1.00						
Funds from oper./Total Debt (%)	0.68	0.75	1.00					
Free Oper Cash Flow/Total Debt %	0.42	0.44	0.61	1.00				
Pre-Tax Return on Avg Capital %	0.66	0.54	0.63	0.37	1.00			
Total Debt / Capitalization %	0.41	0.44	0.68	0.46	0.28	1.00		
Current Ratio (dec.)	0.19	0.19	0.24	0.13	0.09	0.31	1.00	
Size	0.12	0.11	0.02	0.02	0.02	0.03	-0.17	1.00

PANEL B: Correlation matrix for sub components of subjective index

	Industry Position	Competitive Position	Management Quality	Risk Management Policies	Access to Capital
Industry Position	1.00				
Competitive Position	0.40	1.00			
Management Quality	0.44	0.67	1.00		
Risk Management Policies	0.41	0.54	0.61	1.00	
Access to Capital	0.49	0.64	0.67	0.51	1.00

PANEL C: Correlation matrix for information indices

	Objective Index	Performance Index	Size Rating	Subjective Index	Strong Subjective Index	Weak Subjective Index
Objective Index	1					
Performance Index	0.72	1				
Size Rating	0.72	0.04	1			
Subjective Index	0.46	0.22	0.44	1		
Strong Subjective Index	0.42	0.2	0.42	0.78	1	
Weak Subjective Index	0.43	0.22	0.4	0.79	0.77	1

TABLE V

DOES RELIANCE ON SUBJECTIVE AND OBJECTIVE INFORMATION VARY WITH HIERARCHICAL DISTANCE?

This table estimates the credit sensitivity to objective and subjective information variables for firms getting credit approvals at various hierarchical levels within a bank.

Dependent Variable	Log (Approved Credit)			
	(1)	(2)	(3)	(4)
High Level	0.53	0.32	0.15	0.15
	(0.15)	(0.19)	(0.26)	(0.20)
Subjective Index	0.41	0.88	0.00	0.00
	(0.08)	(0.42)	0.00	0.00
Objective Index	-0.04	-0.41	-0.23	0.00
	(0.06)	(0.39)	(0.42)	0.00
Subjective Index * High Level	**-0.43**	**-0.78**	**-0.68**	**-0.54**
	(0.13)	**(0.23)**	**(0.31)**	**(0.31)**
Objective Index * High Level	**0.84**	**0.92**	**0.82**	**0.59**
	(0.13)	**(0.29)**	**(0.28)**	**(0.26)**
Powers of Rule Vars (with Information Interactions)			1	1,2
Loan Officer FE and Information Interactions		Yes	Yes	Yes
No. of Obs.	424	424	424	424
Adj R-sq	0.27	0.39	0.65	0.76

TABLE VI
INFORMATION AND HIERARCHICAL DISTANCE
ADDITIONAL TESTS

This table estimates the credit sensitivity to objective and subjective information variables for firms getting credit approvals at various hierarchical levels within a bank. Columns (1) and (2) also include indicator variables for all 5 levels. Coefficients on Subjective Index, Objective Index, and Level Indicators not reported in columns (1) through (4) for brevity.

Dependent Variable	Log (Approved Credit)			
				Levels 1, 4 And 5 Only
	(1)	(2)	(3)	(4)
Subjective Index * Level 2	**-0.06**	**-0.12**	**0.24**	
	(0.14)	**(0.17)**	**(0.33)**	
Subjective Index * Level 3	**-0.41**	**-0.87**	**-0.76**	
	(0.23)	**(0.31)**	**(0.40)**	
Subjective Index * Level 4	**-0.54**	**-0.91**	**-0.62**	
	(0.23)	**(0.36)**	**(0.42)**	
Subjective Index * Level 5	**-0.32**	**-0.88**	**-0.74**	
	(0.21)	**(0.48)**	**(0.53)**	
Objective Index * Level 2	**0.30**	**0.25**	**-0.25**	
	(0.13)	**(0.14)**	**(0.38)**	
Objective Index * Level 3	**0.86**	**1.13**	**0.92**	
	(0.28)	**(0.40)**	**(0.42)**	
Objective Index * Level 4	**0.98**	**1.37**	**0.70**	
	(0.26)	**(0.39)**	**(0.46)**	
Objective Index * Level 5	**1.17**	**1.14**	**0.57**	
	(0.17)	**(0.38)**	**(0.37)**	
Subjective Index * High Level				**-0.45**
				(0.16)
Objective Index * High Level				**1.12**
				(0.15)
Rule Vars. and Information Interactions			Yes	
Loan Officer FE and Information Interactions		Yes	Yes	
No. of Obs.	424	424	424	212
Adj R-sq	0.33	0.43	0.66	0.48

TABLE VII
GEOGRAPHICAL DISTANCE

Panel A: Joint Distribution of Hierarchical and Geographical Distance

	Level of Approval (Hierarchical Distance)				
Geographical Distance	*1*	*2*	*3*	*4*	*5*
0	113	158	17	0	0
1	0	0	37	57	42

Panel B: Information Use and Geographical Distance

Dependent Variable	Log of Approved Credit		
		Level 3 Only	
	(1)	(2)	(3)
Geographical Distance * Objective	**0.86**	**0.89**	**0.89**
	(0.13)	**(0.45)**	**(0.42)**
Geographical Distance * Subjective	**-0.44**	**-0.36**	**-0.36**
	(0.14)	**(0.38)**	**(0.36)**
No. of Obs.	424	54	424
Adj R-sq	0.27	0.28	0.34

TABLE VIII
DOES EXPERIENCE HELP THE USE OF SUBJECTIVE INFORMATION?

Dependent Variable	Log (Approved Credit)	
	(1)	(2)
Subjective Rating * High Level * Tenure	**2.16**	**2.83**
	(0.56)	**(0.47)**
Objective Rating * High Level * Tenure	**-1.16**	**-1.70**
	(0.65)	**(0.49)**
Rule Vars. and Information Interactions		Yes
Loan Officer FE and Information Interactions	Yes	Yes
No. of Obs.	424	424
R-sq	0.40	0.66

TABLE IX
DECOMPOSING SUBJECTIVE INFORMATION

Dependent Variable	Log (Approved Credit)				
	(1)	(2)	(3)	(4)	(5)
Subjective Index * High Level	**-0.68**	**-0.65**			
	(0.19)	**(0.19)**			
Objective Index * High Level	**0.85**	**0.84**	**0.90**	**0.87**	**0.85**
	(0.25)	**(0.25)**	**(0.13)**	**(0.27)**	**(0.25)**
Weak Subjective Index * High Level			**-0.18**	**-0.29**	**-0.23**
			(0.18)	**(0.21)**	**(0.20)**
Strong Subjective Index * High Level			**-0.40**	**-0.58**	**-0.52**
			(0.19)	**(0.20)**	**(0.19)**
Definition of Subjective Rating	Average	Weighted			
Rule Vars. and Information Interactions	Yes	Yes			Yes
Loan Officer FE and Information Interactions	Yes	Yes		Yes	Yes
No. of obs.	409	409	409	409	409
Adj R-sq	0.73	0.73	0.29	0.42	0.74

APPENDIX B
OBJECTIVE INFORMATION VARIABLES

Objective Information Variable	Mean	SD	Min.	Max.	Obs.
Sub Component of Objective Index (Raw Form)					
Pre-tax Interest Coverage (dec.)	4.60	7.89	-8.36	22.03	405
Pre-tax Funds Flow Interest Coverage (dec.)	7.74	10.59	-6.78	30.28	405
Funds from operations/Total Debt (%)	12.45	35.94	-0.73	121.37	405
Free Oper Cash Flow/Total Debt %	5.22	15.08	-1.24	50.38	405
Pre-Tax Return on Avg Capital %	0.07	0.24	-0.59	0.55	404
Total Debt / Capitalization %	0.42	0.28	0.00	0.92	405
Current Ratio (dec.)	1.23	0.65	0.27	2.80	405
Firm Size	415987	4102722	-102675	84000000	424
Sub Component of Objective Index (Implied Rating)					
Pre-tax Interest Coverage	11.00	7.99	0.00	22	405
Pre-tax Funds Flow Interest Coverage	11.38	7.68	0.00	22	405
Funds from operations/Total Debt (%)	10.25	7.85	0.00	22	405
Free Oper Cash Flow/Total Debt	10.22	8.69	0.00	22	405
Pre-Tax Return on Avg Capital %	9.42	8.67	0.00	22	404
Total Debt / Capitalization %	14.24	6.21	0.00	22	405
Current Ratio	7.04	5.88	0.00	22	405
Firm Size	2.27	1.43	1.00	6	424
Standardized Objective Indices					
Objective Index	0.00	1.00	-1.82	3.26	424
Performance Index	0.00	1.00	-1.73	2.47	424
Size Index	0.00	1.00	-0.89	2.60	424

APPENDIX C
SUBJECTIVE INFORMATION VARIABLES

Subjective Information Variable	Mean	SD	Min.	Max.	Obs.
Industry Risk Assessment					
Trend in Output	3.51	0.80	1	7	409
Trend in Earnings	3.27	0.78	1	7	409
Cyclicality	3.35	0.81	1	7	409
External Risks	3.53	0.71	2	5	409
Mean Category	3.41	0.59	1.75	5	409
Competitive Position					
Market Position	4.28	1.47	1	7	407
Product Line Diversity	3.88	1.12	1	7	408
Operating Cost Advantage	3.46	0.89	1	7	406
Technology Advantage	3.70	0.92	1	7	406
Key Success Factors	3.67	0.84	1	7	406
Mean Category	3.80	0.81	1	7	408
Management					
Professionalism	3.67	0.90	1	7	409
Systems and Controls	3.66	0.89	1	7	409
Financial Disclosure	3.72	0.85	1	7	409
Ability to Act Decisively	3.77	0.80	1	7	409
Mean Category	3.70	0.75	1	7	409
Risk Management Policies					
Leverage Policy	3.34	0.85	1	7	409
Liquidity Policy	3.36	0.86	1	7	409
Hedging Policy	3.60	0.86	1	7	408
Mean Category	3.43	0.72	1	6	409
Access to Capital					
Capital Markets	3.47	1.11	1	7	409
Banks	3.77	1.01	1	7	409
Mean Category	3.62	0.98	1	7	409
Standardized Subjective Indices					
Overall Subjective Index	0.00	1.00	-4	2	424
Strong Subjective Index*	0.00	1.00	-4	4	409
Weak Subjective Index**	0.00	1.00	-3	4	409

*Strong Subjective Index combines Management and Competitve Position
**Weak Subjective Index combines Industry Risk Assessment, Risk Management Policies and Access to Capital

APPENDIX D
SUBJECTIVE INFORMATION VARIABLES - ASSESSMENT CRITERIA

BUSINESS RISK ASSESSMENT

1 *Competitive Position*	RR2	RR3	RR4	RR5	RR6	RR7
Market Position	Below 2% / Minor Player; Declining Share	2 to 3% / Minos Player	Over 5% / Known Player or Established Niche	Over 10% / Major Player or Strong Niche	Over 20% / Dominant	Over 50% / Clearly Dominant
Product Line Diversity	Only 1 Declining Line	Only 1 Stable Line	At least 2 Stable Lines	At least 2 Growing Lines	Over 3 Lines	Over 3 Growing Lines
Operating Cost Advantage	High Cost Producer	No Cost Advantages	Some Cost Advantages	Has Lowest Local Costs	Achieves Low Global Costs	Global Leader
Technology Advantage	Predominantly Outdated	Technology Follower	Mostly New; Upgrading Old	Leader in Local Market	Global Player in Some Areas	Global Leader in Many Areas
Key Success Factors	None	Strong in Some; Weak in Others	Strong Locally in Some Factors	Strong Locally in All Factors	Global Capabilities in Most Factors	Global Capabilities in All Factors

2 *Management*	RR2	RR3	RR4	RR5	RR6	RR7
Professionalism	In Few Positions	At Some Key Positions	At Most Key Positions & Most Levels	At all Key Posi- tions in Operations & Management	At all Levels in Operations & Management	At all Levels With Extensive Experience
Systems and Controls	Largely Absent	Unreliable	Acceptable	Very Reliable and Strong	Meets Highest Local Standards	Meets Highest Global Standards
Financial Disclosure	Unreliable	Delayed, Inaccu-rate or Incomplete	Satisfactory Reporting	Usually Timely and Accurate	Always Timely and Accurate	Meets Highest Global Standards
Ability to Act Decisively	Hopeless	Weak	Good, but Untested	Good, but Untested	Proven to be Strong	Proven to be Very Strong

3 Risk Management Policies	RR2	RR3	RR4	RR5	RR6	RR7
Leverage Policy	Unlimited Appetite	High Tolerance	Some Tolerance	Low Tolerance	Very Conservative	Extremely Conservative
Liquidity Policy	No Policy	Low Liquidity Acceptable	Maintains Some Cushion	Some Cushion & Sound Contingency Plan	Conservative Cushion & Contingency Plan	Extremely Conser-vative Cushion
Hedging Policy	No Hedging Policy / Speculative Policy	Risks Understood but Most Not Covered	Risks Understood but Not Always Covered	Most Risks Understood; Few Open Positions	Most Risks Understood; No Open Positions	All Risks Understood; No Open Positions

4 *Access to Capital*	RR2	RR3	RR4	RR5	RR6	RR7
Capital Markets	No access to Capital markets	Limited Largely to Domestic Banking	Primarily Domes-tic Banking; Some Capital Markets	Primarily Domestic; Some International	Wide Access; Domestic & International	Wide Access; Domestic & International
Banks	Bank Cutting Lines; Some Locked-in	No Bank Strongly Committed or Some Banks Getting Out	At Least One Bank Strongly Committed	At Least One Bank Strongly Committed	Established Re-lationships; Strong Commitments	Established Re-lationships; Strong Commitments

5 *Industry*	RR2	RR3	RR4	RR5	RR6	RR7
Trend in Output	Declining	Uncertain / Declining	Stable	Growth	Strong Growth	Very Strong Growth
Trend in Earnings	Declining	Uncertain / Declining	Stable	Growth	Strong Growth	Very Strong Growth
Cyclicality (Fluctuations)	Large & Unpredictable	Large	Moderate	Small	Very Limited	Very Stable
External Risks	Widespread Risks	Numerous Critical Risks	Variuos Critical Risks	Few Critical Risks	Few Risks, Non Cyclical	No Risks