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Estimating The Effect Of Hierarchies On Information Use

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July 2006

Abstract

We estimate the effect of hiearchical distance on the relative use of subjective and objective information. Credit approved at higher levels (that are more distant from the loan officer who collects information) relies relatively more on objective information and less on subjective information. Using loan-officer fixed effects, and non-linearities in "bank rules" that determine the hierarchical distance for a loan applicant, we show that endogenous assignment of applicants to hierarchical levels or loan-officers to applicants is unlikely to explain our results. The drop in reliance on subjective information at higher levels widens with subjectivity of information. However, the reliance on subjective information at higher levels improves dramatically if the loan approving officer sits in close proximity to the loan officer, or if the loan officer is more experienced.

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The evolution of firms from family businesses into large hierarchical organizations initiated a series of theoretical inquiries into incentives, information flows and issues of control within hierarchies. One of the key questions involves the ability of hierarchies to acquire, transmit and use information that is subjective and more abstract in nature[1].

There is growing consensus that hierarchies are biased against the use of such information that is difficult to collect and transmit. Aghion and Tirole (1997) and Stein (2002) focus on ex-ante incentives and argue that hierarchies discourage collection of subjective information. Sah and Stiglitz (1986), Radner (1993), Bolton and Dewatripont (1994) and Becker and Murphy (1993) highlight reasons that can make the ex-post communication of information more difficult. However, testing whether hierarchies are limited in their ability to use more abstract types of information has alluded empirical work.

This paper investigates the above question using data from the credit folders of a large multinational bank in Argentina. Banking is often the motivating example in theoretical work and thus offers a natural environment for testing how information use varies with hierarchical distance. Our data offers a rare peek inside the workings of a large bank, and the hierarchical decision making process within the bank is particularly suited to the question at hand.

A loan officer sits at the lowest end of the bank's hierarchy and collects a variety of information on a loan applicant. This includes objective information, such as an applicant's return on assets, and subjective information such as the loan officer's assessment of firm quality. For example, an applicant might receive an "A" from the loan officer on "professionalism". The information is then transmitted up the hierarchy to more senior officers who decide the final credit limit suitable for the applicant. We have access to all of the information collected by a loan officer, as well as the final credit approval decision taken by the bank.

A key feature of the loan approval process is that there is variation in the hierarchical position of the final credit approving authority. Some firms are approved at lower level within the hierarchy while others go higher up. This variation in the *hierarchical distance* travelled by a loan application can be used to estimate the effect of hierarchical distance on information use. The hierarchical distance for an applicant is determined ex-ante by a set of pre-specified rules. As we shall describe later, non-

[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".

linearities in these rules permit us to address a number of endogeneity concerns when estimating the direct effect of hierarchical distance on information use.

Our paper begins by outlining a simple model that provides testable predictions that we then take to data. While section I spells out the details, for intuition consider a bank with two hierarchical levels: high and low. A loan officer sits at the lower level and collects two pieces of information concerning firm quality. The first is a subjective signal (say an “A” in “professionalism”), and the other is an objective signal (say a “10%” in ROA). These signals are then used to infer firm quality and to decide how much to lend. All else equal, higher firm quality leads to higher loan approvals. We define *informativeness* of a signal as its covariance with underlying firm quality, which means that signals with higher informativeness will be given more weight by the credit approving officer.

Theories mentioned earlier suggest that informativeness of subjective signal is lower when used at a higher hierarchical level. For example, the loan officer might have less of an incentive to gather good quality information when he knows he is not the decision maker. We therefore get a simple testable prediction: Loan amounts approved at higher levels will be less sensitive to subjective information and more sensitive to objective information *relative to* loans approved at lower levels.

Evidence from our sample of 424 corporate loan applicants is consistent with the model’s prediction. We find that sensitivity of approved loan amount to subjective information drops while sensitivity to objective information increases when loans are approved at higher levels.

However one may be concerned that this result is driven by endogenous assignment of firms to different levels for approval. For example, perhaps larger and well-established firms are more likely to be sent to higher levels for approval *and* these are also the firms that intrinsically have less relevant subjective information. Then officers at higher levels will put less weight on subjective information - even if say communication were perfect - because firms assigned to them have naturally low subjective information.

To account for such *bank selection criteria* concerns, we take advantage of the fact that allocation of firms to various approval levels is based on a set of pre-specified rules outlined in the bank’s credit manual. These rules are based on some hard firm characteristics such as industry, size, etc. The assignment rules are a non-linear function of these applicant characteristics. Therefore, we can control for linear and other higher powered functions of the bank selection criteria variables and only exploit the non-linearities for identification which are less likely to suffer from the endogeneity concern.

There may also be a *firm self-selection* concern that applicants wishing to be approved at a particular level manipulate their attributes so as to get assigned to that level. Since manipulating own attributes is costly, such self-selected firms are likely to lie on the margin between high and low approval levels. Therefore by dropping firms on the margin between levels, we show that our results cannot be driven by this concern either.

A final *loan officer selection* concern is the endogenous assignment of loan officers to loan applicants. For example, it could be the case that firms approved at lower levels by loan officers themselves are assigned to more talented loan officers with better ability to extract subjective information. In such a scenario, loan officers deciding on credit approvals will put more weight on subjective information because of their higher ability in collecting subjective information, and not because of any effect of hierarchical distance on subjective information. However, since we know the identity of loan officers, we control for this concern non-parametrically using loan officer fixed effects. The fixed effects force 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 these endogeneity concerns: Credit sensitivity to subjective information is smaller, while credit sensitivity to objective information is larger for firms approved at higher levels. We also 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. The change in information sensitivity (for both subjective and objective information) is not gradual over the five layers, but occurs suddenly between levels 2 and 3.

These sharp changes in information sensitivity are driven by differences in the geographical location of bank officers. Loan officer at levels 1 and level 2 bank officer always sit in the same local bank branch, while officers at level 4 and 5 always sit outside the local branch. The officer at level 3 may or may not sit in the local branch. We show that the changes in information sensitivity occur at level 3 only when the level 3 officer sits outside the local branch. If the level 3 officer also sits in the same branch as the loan officer, then the change in sensitivity occurs at level 4.

The geographical location results suggest that close proximity with the loan officer (who collects information) helps in understanding and transfer of subjective information through repeated interactions. 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. Senior bank officers might be better able to understand and "decode" subjective information from more experienced loan officers as a result of repeated interactions with them.

Finally, we find that our results are stronger the more subjective a piece of information is. We decompose our aggregate index of subjective information into its constituent parts, and find that the decline in subjective information sensitivity is larger for more subjective sub-components.

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 in the decision making process 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. For example, our results may be due to the loan officer investing less effort in the collection of subjective information (a la Aghion and Tirole (1997) and Stein (2002)), or they might reflect higher ex-post communication costs for subjective information as in Bolton and Dewatripont (1994) or others cited earlier.

There is a strand of empirical literature that links costs associated with communication of soft information to the scope of a bank's business activities. Recent work by Berger et al (2005) and Mian (2006) shows that small banks and local banks with flatter organizational structures are better at relationship banking activities that require the use of more abstract types of information. However, the evidence in these papers only indirectly links hierarchical distance with difficulty in using soft information. 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. One strand of this literature such as Aghion and Tirole (1997) and Stein (2002) focuses on incentives. It argues that large hierarchical systems inhibit incentives to collect information (particularly subjective or soft information) because of a lack of discretion given to those in charge of collecting information at low levels. Others such as Radner (1993), Bolton and Dewatripont (1994) and Becker and Murphy (1993) focus more on the costs of communication, and argue 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.

Although theories based on incentives and costly communication differ in their details and focus, they share some common predictions. The key prediction is that information generated at lower levels loses "informativeness" when used at higher levels for decision making.

For example, incentive theories suggest that when lower level employees, responsible for collecting information, know that someone else has discretion on how their information is used, they put less effort in information collection. Correspondingly if information is used by lower level employees themselves, it will be of higher quality (or informativeness) compared to when information is used at higher levels. Similarly theories based on costly communication suggest that as information is passed up the hierarchical chains, it loses part of its informativeness and hence becomes less and less useful.

Theory also predicts that the loss in informativeness across hierarchies, whether driven by incentives or costly communication, is particularly strong when information is more intangible or subjective in nature. Such information is at times referred to as soft information[2]. Thus a more refined theoretical prediction is that as information travels up a hierarchy, subjective information loses informativeness more than objective information.

Taking this theoretical prediction to data 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

[2] See Petersen (2004) for a comprehensive discussion of different types of information used in the literature.

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. In particular a loan officer knows before grading a firm that he himself will be using the information, he might put a lot of effort in ensuring its quality. However, if he knows that the information will be used by someone higher up who might even discard his information, the loan officer will have less of an incentive to maintain quality (as in Stein (2002)). Thus the "A" going to a manager might be a poor signal[3].

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

[3] 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.

$L(Q)$, 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[4]. 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 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

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

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.

The theory has no prediction on the level of sensitivity to subjective and objective information. In terms of 3, there is no particular prediction on the relative magnitude of coefficients β_H and β_S.

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 429 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[5] 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

[5] 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.

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 is important since 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[6]. There are 5 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 positive year for Argentina in terms of macro-economic activity and before the

[6] There might still be some room for the loan officer to indirectly manipulate how firms are assigned to different levels of hierarchy. We shall discuss these issues in greater detail in the next section.

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[7] 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. There are 19 such variables and Table I shows their summary statistics. We provide descriptive statistics for those that statistically significant in the analysis[8].These variables include net worth of the firm, years in industry, length of firm-bank relationship, firm classification by central bank, whether the firm has ever reneged covenants, any negative auditor remark, sharp changes in the firm's industry, etc. As has already been emphasized, none of these variables is subjective or based on the discretion of the loan officer. The rule variables are then used to map firms to different hierarchical levels according to the rules specified in the bank's credit manual.

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, firms requesting larger loans 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 firm age, length of relationship with bank, firm industry and credit score can send a firm to higher levels for approval

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

[8] Eleven rule variables have enoughstatistical variation in the sample of 424 firms. There is not enough variation in the other 8 rule variables.For brevity we do not report their summary statistics. These variables are (in parenthesis the number of firms in each category): Amount Over Maximum Limit (1), Downgrade in FRR Since Last Review (19), Risk Event At The Company (1), Adverse Change In Risk Profile (8), Adverse Change In Critical Success Factors (1), Covenant Violations (6), Qualified Auditors' Opinion (4) and Override In Debt Rating Model (13).

even if the firm falls in a lower level according to amount requested. 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. The pattern once again reflects 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 firms requesting larger loans, troubled firms, firms with more complex loan requests and firms belonging to volatile or nascent industries are more likely to 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 the 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 0.49. 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 rule variables as well, but R-sq does not increase by much, just to 0.50. Column (3) adds some non-linear functions of the rule variables by including functions of powers 2 and 3 for the rule variables. The R-sq increases slightly to 0.53 as a result[9]. 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 0.43 vs. 0.49 in column (1)). In a regression

[9] In Columns (2) and (3) Significant Increase In Facilites and Company Out Of Risk Acceptance are dropped from the regressions due to multicollinearity with other variables.

not reported I also include the next two top rule variables to those in column (4). In this particular case the R-sq reaches 0.47 against 0.49. Therefore, the 19 rules variables can be summarized into only 6.

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) as well. 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 firm level information. Loan officers collect objective information from audited financial statements and also visit the firm's management and premises to collect subjective information such as management and business quality. A typical loan officer manages around 20-25 firms (on average) that are mostly clustered in a single or related industries[10].

The bank pre-specifies what pieces of information have to be collected by a loan officer. Following Petersen (2004), we classify the information collected as "objective" if it consists of quantifiable measures that are easy to collect, store, and transmit. Objective variables can also be verified by a third party at little or no cost. Such variables include audited firm financials such as net-worth, size, interest coverage and return on assets. The bank summarizes the objective variables into an overall "objective risk rating" index and two sub-indices using a credit scoring model. The first sub-index is a financial risk rating index that uses financial ratios to summarize the financial health of the firm. The second is a size ranking that ranks firms according to their asset base and net worth. Table I provides a summary of the objective information variables as well as the two indices constructed by the bank using these variables. Appendix A provides a full description of all the objective variables collected by the loan officer.

The second category of informational variables collected by the loan officer are subjective variables. These are personal assessments of the loan officer that are difficult to transmit and costly to verify by a third party. The bank pre-specifies what subjective firm attributes a loan officer must assess. The loan officer then assigns a score of 1 through 7 to each subjective firm attribute. Subjective attributes include management quality, accounting practices, firm's risk management policies, firm's

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

overall market positioning, industry outlook and firm's access to external capital markets. Appendix B provides full description and summary statistics for each subjective criteria. The numerical categories are arranged in a way that larger numbers signify better firm quality. The bank also aggregates its subjective information into an index of overall business assessment that we will refer to as "subjective risk rating".

Table I provides summary statistics for all subjective information variables. Although these variables are all classified as subjective, 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 shall discuss such heterogeneity in subjectiveness in the results section.

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. 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

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 describe our methodology for addressing each concern.

1. Bank Selection Criteria:

Identification of equation (3) would work best if the bank allocated 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 the importance of hard and soft information. For example, suppose that firms with less reliable subjective information are deliberately sent further up in the hierarchy for approval 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 in the hierarchy for approval, 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 firm 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 then is that larger firms might have less relevant subjective information, i.e. σ_{qs}^2 is lower for larger firms for any given level of effort put in by a loan officer. If this were the case then β_S^M 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 $\overline{\sigma_{qh}^2}$ and $\overline{\sigma_{qs}^2}$ denote the maximum possible informativeness of objective and subjective information for a firm, i.e. the informativeness that a loan officer would generate if he works efficiently. Then the general concern is that any bank selection criteria Z might be positively correlated with $\overline{\sigma_{qh}^2}$ and/or negatively correlated with $\overline{\sigma_{qs}^2}$. Figure III plots some possible relationships between Z and $\overline{\sigma_{qs}^2}$, and Z and $\overline{\sigma_{qh}^2}$ that can bias β_S^M downwards and β_H^M upwards respectively.

The bank selection concern highlighted in figure III is almost impossible to address if Z is unknown or not observable. However, as has already been 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 objective criteria not subject to the loan officer's direct discretion. We can therefore control for bank selection 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 in bank selection controls.

The inclusion of linear and quadratic bank selection controls implies that the identification of β_H^M and β_S^M 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 discontinuous function of the ex-ante firm selection variables. Once we control for linear and quadratic components of Z, it is these discontinuities and "jumps" in the residual variance that are used to identify β_H^M and β_S^M.

2. Loan Officer Selection:

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 collecting information had an advantage in collecting subjective information.

However we know the identity of the loan officer collecting information for each firm and hence we can fully address the loan officer selection concern by including loan officer fixed effects, and interacting these fixed effects with H and S. The 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:

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

3. Firm Self Selection:

Even though the 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. This self-selection of firms is only a concern from identification perspective if firms with inherently better quality subjective information want to be approved by lower level officers. This in turn might happen if firms with inherently better quality subjective information *know* that lower level officers are better at using subjective information. Thus firm self-selection is only a concern if an effect of hierarchies on information use exists in the first place. Firm self-selection might overstate an existing effect, but it is hard to generate an effect if none exists.

Manipulating own attributes is likely to be costly for firms. 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 their deviation from true demand is likely to hurt the firm. Therefore if firms do manipulate own information to get assigned to a lower (or higher) approval level they would manipulate information just enough so that they qualify for the desired level right on the margin. This suggests that self-selected firms are likely to lie on the margin of different approval levels.

There is thus a simple way to test if firm self selection is driving the main coefficients of interest. If we drop firms on the margin between high and low approval levels, then the remaining firms are unlikely to suffer from self selection concerns.

IV. Results

A. Effect of Hierarchy on Information Use

The main regression specification (3) can be tested using the methodology and data described above. We begin by collapsing the 5 approval levels into "high" and "low" around the median. In particular, we classify approval levels 1 and 2 as "low", while levels 3, 4 and 5 are classified as "high". Column (1) of Table IV estimates equation (3) using log of approved credit line as the dependent variable. Coefficients on interaction terms indicate 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 the high level.

The results are consistent with theoretical prediction highlighted in proposition 1. However as section III explained, these result may also be driven by endogenous selection of firms and/or loan officers. We control for bank's selection criteria first by including variables used by the bank to assign firms to different levels as controls. Column (2) includes these rule variables and their interactions with objective and subjective information indices as controls. Column (3) 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. 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 selection criteria.

The increase in sensitivity to objective information is very similar in magnitude to the drop in sensitivity to subjective information at high levels: -0.45 vs. 0.36 and -0.73 vs.0.59 in columns (1) and (2) respectively. Adding non-linearities to column (3) does not change the magnitude and direction of the coefficients.

Column (4) addresses the endogenous loan officer selection concern as well by incorporating loan officer fixed effects and interactions of these fixed effects with hard and soft information indices. Column (4) thus runs the updated estimation equation (4) highlighted earlier. The fixed effects approach controls for the person generating subjective and objective information non-parametrically and isolates variation in the level of approval for firms whose credit folders were put together by the *same* loan officer. There are a total of 26 loan officers collecting information for the 424 firms in our sample. Column (4) shows that our main results are completely robust to the fixed effects specification as well.

Table IV had collapsed the 5 hierarchical levels into two. Columns (1) and (2) in Table V open up the 5 levels to see how sensitivity to information changes at each level. Column (1) includes bank selection criteria variables and their interactions, while column (2) adds loan officer fixed effects and their interactions 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) and (2) also suggest a way to control for the remaining endogeneity concern, *i.e.* firm self-selection. As discussed in the previous section, firm self selection is a concern for firms at the margin between 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 firm self-selection by dropping firms belonging to level 2 and 3. Column (3) runs the primary regression specification (3) on 212 firms belonging to levels 1, 4 and 5, with level 1 firms classified as "low" and firms belonging to levels 4 and 5 classified as "high". The results are very similar to those found earlier, showing that firm self-selection is an unlikely explanation of our findings. Column (4) repeats the analysis of column (3) after incorporating bank selection criteria variables and loan officer fixed effects as controls as well. The results are robust to these controls as well.

Another way to control for firm self selection is to go through the credit manual rules and identify firms that are unlikely to have any room to manipulate their approval level. For example, those firms with foreign guarantees (firms' headquarters securing the Total Facility) do not go to beyond level 3. Restricting our analysis to these firms, we repeat our primary analysis in column (5) and (6). Once again the results are robust to this sample restriction. In a regression not reported we also restricted our analysis to those firms with Amount Requested below $0.5 million. Results are also robust to this sample restriction. In all the controls and sample selection tests of Tables IV and V suggest that endogenous firm selection whether driven from the bank side or by firms themselves is unlikely to drive our results. Similarly endogenous loan officer assignment by the bank cannot explain our results either, suggesting that they are likely driven by the direct effect of hierarchies on information use.

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 different from approval at level 3, but not different 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. The information shows that loan officers (who sit at level 1) and 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 could reflect the possibility that communicating subjective information among co-worker 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 sit both inside and 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 can exploit variation in location of the loan approving officer to formally test whether results in Table IV were driven by the loss in informativeness due to officers sitting at different geographical locations. Columns (1) of Table VI runs the primary regression but instead of using approval levels, uses location of the approving officer as the hierarchical measure. 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, since there is no variation in geographical locations within levels 1, 2, 4 and 5, only level 3 firms offer an opportunity to perform an independent test of geographical location. 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[11]. Column (3) adds bank selection criteria controls and the results are qualitatively unchanged.

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. 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 VII repeat the primary regression specification but replace subjective information rating with AVGsubjective and WAVGsubjective re-

[11] 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.

spectively. 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. The bank creates subjective information variables in five categories: industry outlook, risk management policies, access to capital, competitiveness, and management quality. Columns (3) through (7) put these five subjective information categories and their interactions with high level separately on the right hand side. Column (8) puts all the five categories and their interactions together. Since some of the categories are collinear, coefficients are not very significant.

However an interesting trend can be seen from columns (3) through (8). Credit sensitivity to three subjective information categories, i.e. industry outlook, risk management policies and access to capital does not decline significantly at high levels. Sensitivity to the remaining two subjective categories does decline. The three categories that do not decline are also categories that are relatively "less subjective". For example 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 variables linked to a firm's competitiveness and management quality are more subjective. These variables are more subjective in their construction. For instance, ranking a firm's "professionalism", "ability to act decisively", or "technology advantage" is inherently a subjective exercise.

We therefore divide the subjective information variables into less and more subjective categories and test whether the drop in credit sensitivity to subjective information at higher approval levels is more pronounced for more subjective variables. Column (9) shows that more subjective variables experience a larger decline in credit sensitivity at higher levels. This lends further support to the view that it is the subjectivity of information that makes it difficult to be communicated across hierarchies.

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).

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

If the decline in subjective information sensitivity at high levels is driven by costly communication, then one might expect the decline to shrink when the loan officer is more experienced. 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. For example, a job market recruitment committee might give more weight to a recommendation if they have personally interacted with the recommending professor often. One might expect similar results if the results were driven by differential incentives for the loan officer.

To test if the experience of a loan officer helps facilitate subjective information communication, we use our loan officer fixed effects specification and then triple interact 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.

V. Discussion of Results

Results in Section IV indicate that hierarchical level of approval does have an independent effect on the negative use of subjective versus objective information. We saw that these results are unlikely to be driven by endogenous assignment of firms to approval levels, or of loan officers to firms. The fact that our effect kicks in when approving officer sits in a different geographical location than the loan officer further indicates the importance of organizational design on information use. In this section we outline some possible economic interpretation of our results.

These interpretations are not mutually exclusive and our results may be driven by more than one interpretation.

A. Loss in Communication

As already discussed in section I, 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

There could be a concern that when a loan officer knows that he does not have control over approval decision, he might deliberately provide inaccurate information to higher up officials. This might be done for strategic reasons so that the bank gives more control in the hands of loan officers, or it might be done to make the decisions of other officers look worse. While objective information is difficult to manipulate due to its objective nature, manipulation is easier with subjective information as it is based on the subjective views of a loan officer. Therefore if 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. Even if such 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.

VI. Concluding Remarks

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. Some 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. Our access to the credit folders of a large hierarchical bank gave us a rare opportunity to peek inside the decision making process of a hierarchy. Using information collected by the bank’s loan officers at the lowerst level, we measured how officers at various hierarchical levels “embed” the different types of information in their loan approval decisions. The set of pre-specified rule used by the bank for assigning applicants to approval levels, as well as other details of data, enabled us to control for a number of endogeneity concerns. While we find that greater hierarchical distance inhibits the use of subjective and more abstracts types of information, other factors such as geographical proximity and frequency of past interactions can help alleviate these constraints.

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Figure I:
An Example of Bank Hierarchical Structure

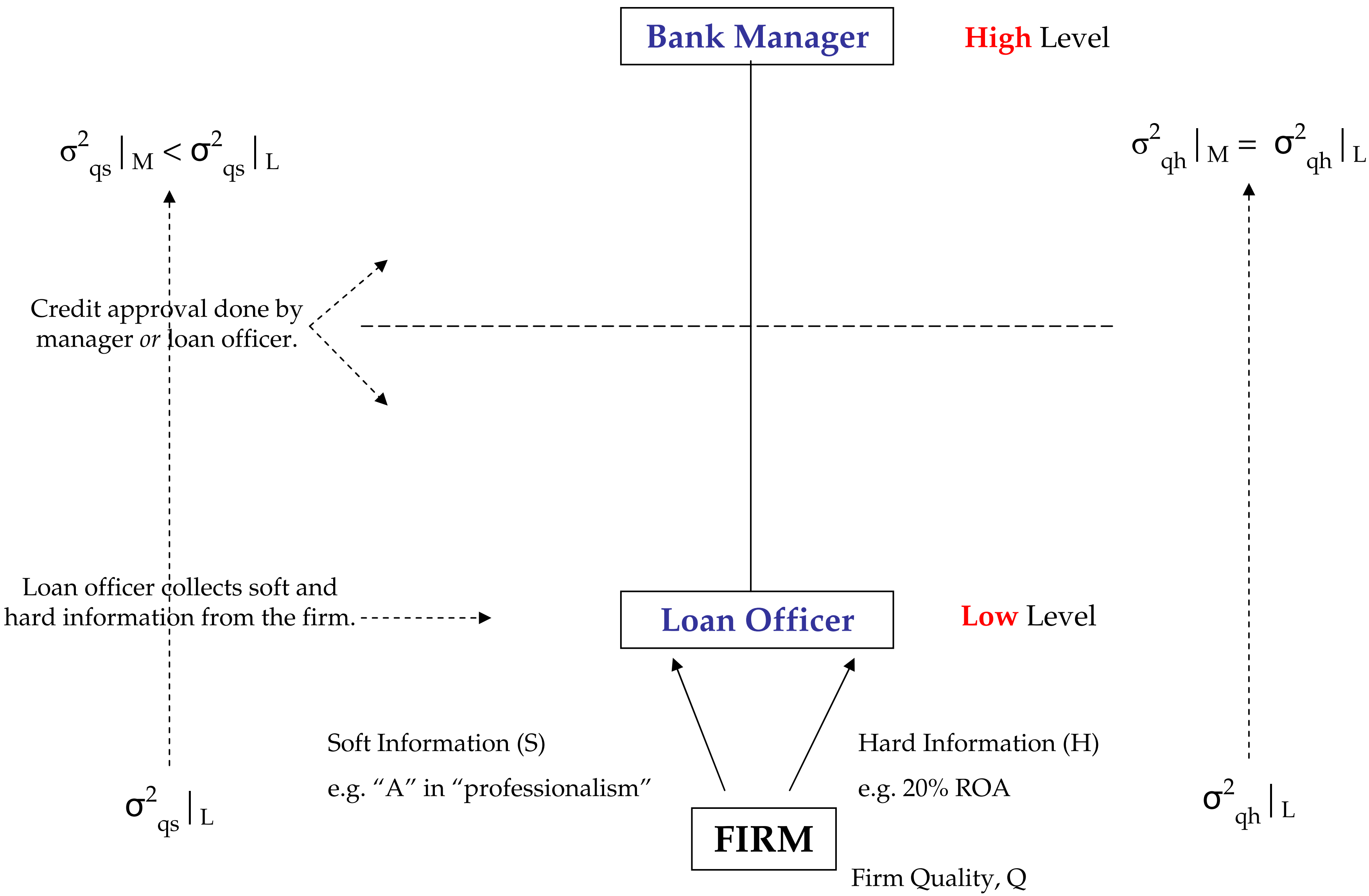

Figure II:
Hierarchical Decision-Making Process

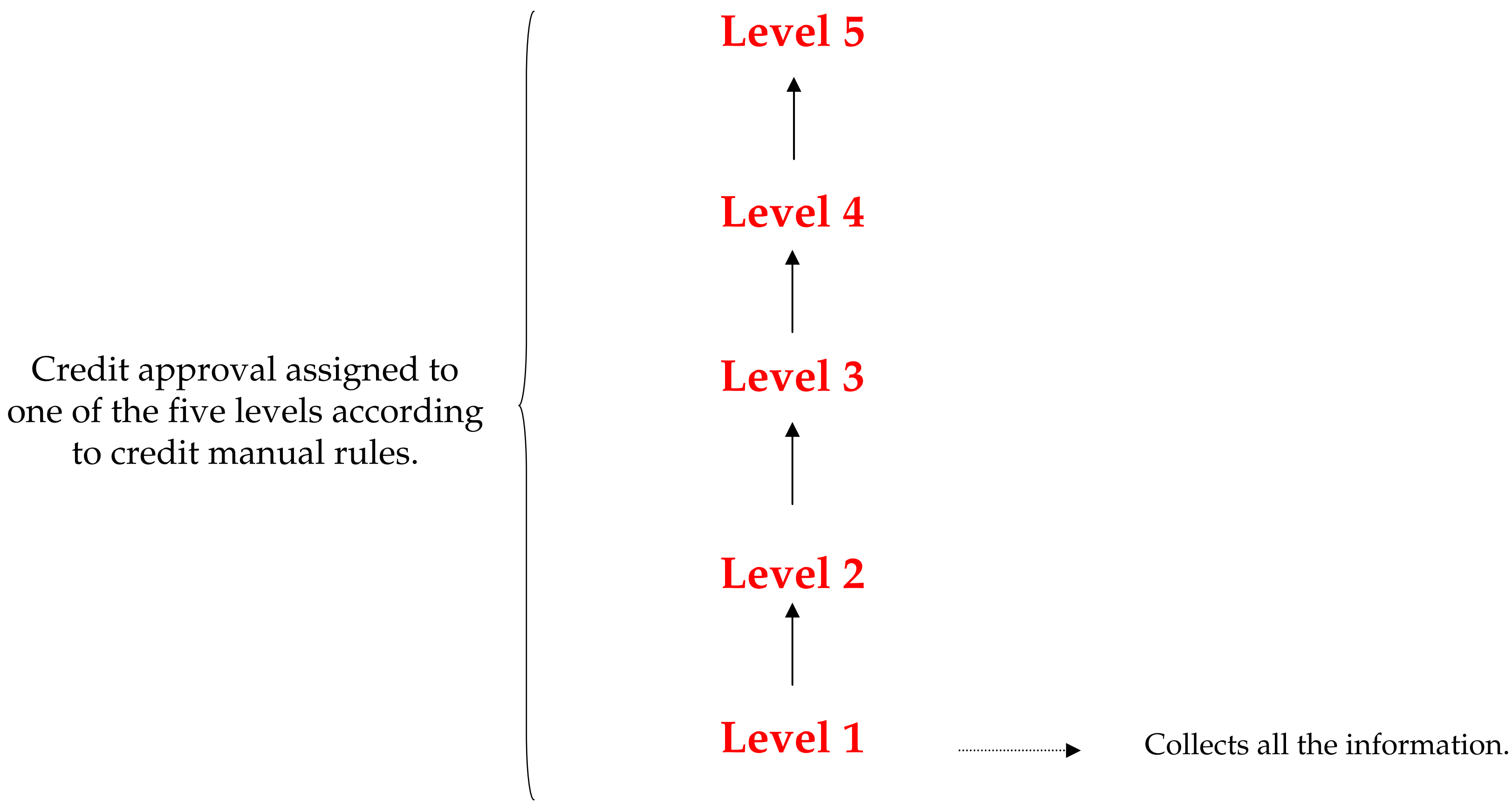

Figure III: Empirical Strategy

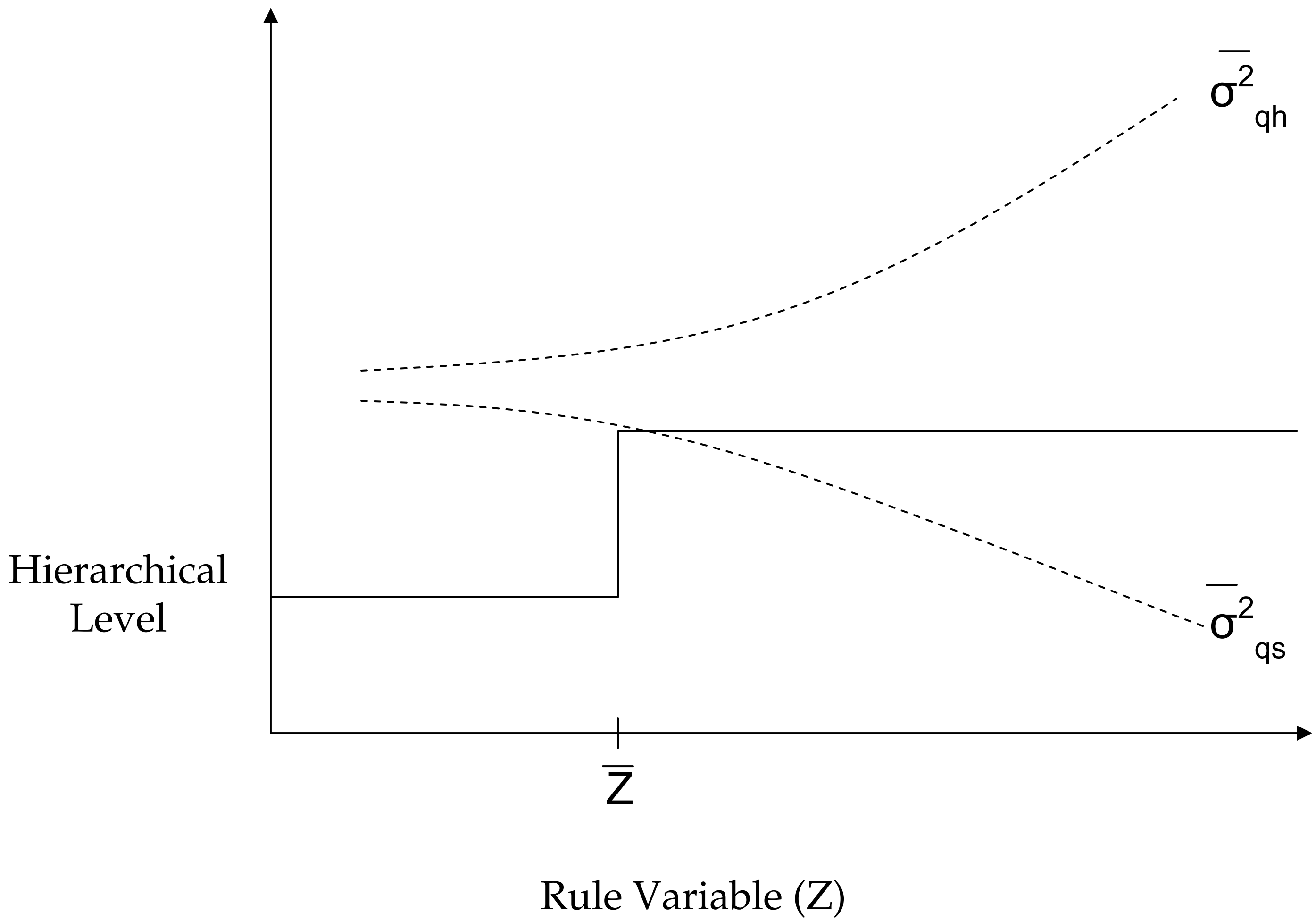

TABLE I
SUMMARY STATISTICS

Variable	Mean	SD	Min.	Max.	Obs.
Approval Level Indicator Variables					
Level 1	26.6%				113
Level 2	37.4%				158
Level 3	12.7%				54
Level 4	13.4%				57
Level 5	9.9%				42
Approval Level Rule Variables (*)					
Facility Risk Rating (FRR)	12.39	4.15	1.00	22.00	424
Central Bank Credit Score	1.20	0.59	1.00	4.00	424
Amount Requested (in Million $)	19.86	34.81	0.00	362.00	424
Foreign Guarantees	0.23	0.42	0.00	1.00	424
Company Out Of Target Market	0.27	0.44	0.00	1.00	424
Company Out Of Risk Acceptance	0.16	0.36	0.00	1.00	424
Significant Increase in Total Facilities	0.02	0.13	0.00	1.00	424
Adverse Change in Industry Outlook	0.06	0.24	0.00	1.00	424
Family Company?	0.16	0.37	0.00	1.00	424
Years in Industry (logs)	7.52	1.28	0.00	9.08	424
Length of Relationship (logs)	2.49	1.37	0.00	4.98	424

*Reported only those rule variables that are statistical significant.

TABLE I (Continued)
SUMMARY STATISTICS

Variable	Mean	SD	Min.	Max.	Obs.
Objective Information Variables					
Pre-tax Intererst Coverage	-2.05	91.12	-1316.00	284.11	424
Pre-tax Funds Flow Intererst Coverage	2.49	81.70	-1254.50	322.87	424
Funds from Operations/Total Debt (%)	13.68	49.38	-27.74	700.00	424
Free Oper. Cash Flows/Total Debt (%)	15.19	204.09	-21.59	4100.00	424
Pre-tax Return on Average Credit (%)	0.23	2.99	-30.29	23.25	424
Total Debt/Capitalization (%)	0.39	0.83	-14.27	4.71	424
Current Ratio	1.37	1.32	0.00	13.42	424
Size Rating	2.30	1.44	1.00	6.00	424
Financial Risk Rating	9.62	4.97	1.00	20.00	424
Objective Risk Rating [1-7]	3.86	1.27	0.50	7.00	424
					424
Subjective Information Variables					424
Industry Position	3.41	0.59	1.75	5.00	424
Competitive Position	3.80	0.81	1.00	6.60	424
Management Quality	3.70	0.75	1.00	6.50	424
Risk Management Policies	3.43	0.71	1.00	6.33	424
Access to Capital	3.62	0.98	1.00	7.00	424
Subjective Risk Rating [1-7]	3.47	0.66	1.00	7.00	424
Other Variables					
Total Facilities (in Million $)	16.61	28.77	0.00	260.88	424
Total Facilities Prev.Year (in Million $)	14.99	28.07	0.00	247.50	424
Total Outstanding (in Million $)	10.74	21.51	0.00	172.53	424
Net Sales (in Million $)	225.59	519.29	0.00	5500.00	424
Net Income (in Million $)	9.83	52.76	-157.59	580.00	424
Leverage	3.43	11.76	0.00	119.90	424

TABLE II
SUMMARY STATISTICS OF VARIABLES BY APPROVED LEVELS

	Mean				
Variable	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Approval Level Rule Variables					
Facility Risk Rating (FRR)	9.61	11.89	14.37	14.43	16.40
Central Bank Credit Score	1.06	1.09	1.24	1.23	1.88
Amount Requested (in Million $)	6.53	17.19	17.54	41.42	42.00
Foreign Guarantees	0.74	0.02	0.01	0.00	0.00
Company Out Of Target Market	0.13	0.10	0.50	0.61	0.50
Company Out Of Risk Acceptance	0.02	0.05	0.35	0.40	0.33
Significant Increase in Total Facilities	0.00	0.00	0.07	0.00	0.07
Adverse Change in Industry Outlook	0.04	0.02	0.24	0.09	0.00
Family Company?	0.06	0.07	0.44	0.25	0.29
Years in Industry (logs)	7.45	7.43	7.80	7.74	7.37
Length of Relationship (logs)	2.25	2.39	2.71	2.85	2.76
Objective Information Variables					
Size Rating	1.48	2.00	2.60	3.77	3.39
Financial Risk Rating	9.84	9.32	11.67	9.39	7.95
Objective Risk Rating [1-7]	3.45	3.74	4.50	4.43	4.00
Subjective Information Variables					
Industry Position	3.35	3.28	3.46	3.62	3.70
Competitive Position	3.69	3.70	3.83	4.00	4.11
Management Quality	3.40	3.64	3.85	4.00	4.11
Risk Management Policies	3.35	3.39	3.46	3.52	3.65
Access to Capital	3.31	3.52	3.81	4.06	3.93
Subjective Risk Rating	3.26	3.41	3.48	3.84	3.74
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
Leverage	3.64	4.63	1.86	2.42	1.70

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 rule variables listed in Table I. However, for brevity we only report coefficients of variables with a t-stat of over 1.95. Regressions are run on the 424 firms in our sample.

Dependent Variable	Approval Level					
	OLS				Ordered Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
Facility Risk Rating	0.06	0.11	-0.16	0.08	0.08	0.19
	(0.01)	(0.03)	(0.15)	(0.01)	(0.02)	(0.10)
Central Bank Credit History	0.37	0.90	6.25	0.38	0.37	1.10
	(0.09)	(0.64)	(2.87)	(0.09)	(0.12)	(0.57)
Amount Requested	0.01	0.01	0.03	0.01	0.01	0.02
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign Guarantees	-0.94	-0.67	-0.89	-1.09	-1.94	-2.03
	(0.12)	(0.48)	(0.12)	(0.13)	(0.19)	(0.20)
Company Out Of Target Market	0.35	0.01	0.33		0.26	0.22
	(0.13)	(0.91)	(0.13)		(0.16)	(0.16)
Company Out Of Risk Acceptance	0.59	1.16			0.61	0.55
	(0.15)	(1.64)			(0.18)	(0.18)
Significant Increase in Facilities	1.05				1.08	0.93
	(0.36)				(0.43)	(0.43)
Adverse Change in Industry Outlook	-0.53	0.79	-0.61		-0.57	-0.59
	(0.21)	(2.05)	(0.20)		(0.24)	(0.25)
Interaction Of Rule Variables		Yes				
Powers 2 and 3 of Rule Variables included?			Yes			Yes
No. of Obs.	424	424	424	424	424	424
Adj R-sq / Pseudo R-sq	0.49	0.5	0.53	0.43	0.21	0.26

TABLE IV
APPROVAL LEVEL AND CREDIT SENSITIVITY TO INFORMATION

This table estimates the credit sensitivity to hard and soft information variables for firms getting credit approvals at various hierarchical levels within the organizational structure under analysis.

Dependent Variable	Log (Approved Credit)			
	(1)	(2)	(3)	(4)
High Level	0.89	0.61	0.72	2.01
	(0.77)	(0.96)	(0.96)	(1.55)
Subjective Rating	0.70	0.16	-0.08	-1.07
	(0.12)	(0.40)	(1.01)	(1.97)
Objective Rating	-0.11	0.33	-0.51	0.60
	(0.06)	(0.18)	(0.44)	(0.83)
Subjective Rating * High Level	-0.45	-0.73	-0.74	-1.03
	(0.22)	(0.27)	(0.35)	0.54
Objective Rating * High Level	0.36	0.59	0.58	0.51
	(0.10)	(0.17)	(0.17)	(0.24)
Powers of Rule Variables and their interactions with Hard and Soft Ratings.		1	1, 2	1,2
Loan Officer Fixed Effects and their interactions with Objective and Subjective Ratings	No	No	No	Yes
No. of Obs.	424	424	424	424
Adj R-sq / Pseudo R-sq	0.22	0.30	0.32	0.43

TABLE V
APPROVAL LEVEL AND CREDIT SENSITIVITY TO INFORMATION
ADDITIONAL TESTS

This table estimates the credit sensitivity to hard and soft information variables for firms getting credit approvals at various hierarchical levels within the organizational structure under analysis. We also provide robustness checks on the sample used in each of the tests. Regressions include indicator variables indicator variables for all 5 levels in columns (1) and (2).

Dependent Variable	Log (Approved Credit)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subjective Rating	-0.01	-0.86	0.63	0.39	0.71	0.42
	(0.35)	(0.97)	(0.13)	(0.48)	(0.14)	(0.52)
Objective Rating	0.32	0.01	-0.19	0.14	-0.11	0.06
	(0.18)	(0.43)	(0.09)	(0.24)	(0.07)	(0.29)
Subjective Rating * Level 2	0.09	0.13				
	(0.23)	-0.23				
Subjective Rating * Level 3	-0.83	-0.91				
	(0.42)	(0.43)				
Subjective Rating * Level 4	-0.49	-0.43				
	(0.34)	(0.39)				
Subjective Rating * Level 5	-0.79	-0.62				
	(0.40)	(0.59)				
Objective Rating * Level 2	-0.15	0.14				
	(0.13)	(0.15)				
Objective Rating * Level 3	0.87	0.92				
	(0.27)	(0.28)				
Objective Rating * Level 4	0.41	0.43				
	(0.20)	(0.21)				
Objective Rating * Level 5	1.03	1.13				
	(0.19)	(0.19)				
High Level			1.28	0.30	0.31	0.19
			(1.03)	(1.96)	(0.46)	(1.05)
Subjective Rating * High Level			-0.52	-0.60	-1.19	-1.38
			(0.27)	(0.37)	(0.14)	(0.38)
Objective Rating * High Level			0.49	0.89	1.57	1.69
			(0.13)	(0.24)	(0.07)	(0.14)
Powers of Rule Variables and their interactions with Obj./Sub. Ratings.		Yes		Yes		Yes
Loan Officer Fixed Effects and their interactions with Obj./Subj. Ratings	No	Yes	No	Yes	No	Yes
No. of Obs.	424	424	212	212	224	224
Adj R-sq / Pseudo R-sq	0.35	0.40	0.39	0.55	0.24	0.48

TABLE VI
GEOGRAPHIC DISTANCE

Dependent Variable	Log of Approved Credit		
	All Levels	Only Level 3	
	(1)	(4)	(5)
Objective Rating	0.27	0.65	0.74
	(0.09)	(0.22)	(0.27)
Subjective Rating	0.25	-0.38	-0.29
	(0.20)	(0.47)	(0.59)
In Headquarters	-0.87	0.93	1.56
	(0.82)	(1.64)	(1.85)
In Headquarters* Objective	-0.35	-0.70	-0.72
	(0.11)	(0.28)	(0.34)
In Headquarters* Subjective	0.44	0.67	0.62
	(0.23)	(0.44)	(0.42)
Powers of Rule Variables and their interactions with Objective and Subjective Ratings.			Yes
No. of Obs.	424	54	54
Adj R-sq / Pseudo R-sq	0.21	0.26	0.50

TABLE VII
DECOMPOSING SUBJECTIVE INFORMATION

Dependent Variable	Log (Approved Credit)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subjective Rating/Measure	0.87	0.92	0.42	0.51	0.68	0.30	0.56		
	(0.21)	(0.21)	(0.16)	(0.09)	(0.11)	(0.11)	(0.10)		
Objective Rating	0.06	0.05	0.05	0.04	0.05	0.06	0.02	0.21	0.05
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.67)	(0.10)
Subjective Rating * High Level	-1.14	-1.13							
	(0.23)	(0.23)							
Objective Rating * High Level	0.33	0.33	0.22	0.27	0.27	0.21	0.26	0.38	0.33
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Industry * High Level			-0.42					-0.45	
			(0.32)					(0.38)	
Competitive Position * High Level				-0.51				-0.48	
				(0.16)				(0.21)	
Management* High Level					-0.61			-0.54	
					(0.16)			(0.25)	
Risk Management * High Level						-0.34		-0.18	
						(0.26)		(0.20)	
Access Capital * High Level							-0.45	0.00	
							(0.12)	(0.17)	
Less Subjective Score (Objective)									0.44
									(0.26)
More Subjective Score (Subjective)									0.46
									(0.20)
Less Subjective Score * High Level									-0.42
									(0.37)
More Subjective Score * High Level									-0.67
									(0.30)
Definition of Subjective Rating	Average	Weighted	Industry	Competition	Management	Risk Management Policies	Access Capital	All	Obj/Sub
Definition of Objective Rating	Bank's	Bank's	Bank's	Bank's	Bank's	Bank's	Bank's	Bank's	Bank's
Powers of Rule Variables and their interactions with Objective and Subjective Ratings.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	409	409	409	409	409	409	409	409	409
Adj R-sq / Pseudo R-sq	0.38	0.38	0.29	0.33	0.33	0.33	0.35	0.50	0.38

TABLE VIII
IMPACT OF HUMAN CAPITAL

Dependent Variable	Log (Approved Credit)	
	(1)	(2)
Subjective Rating	0.76	0.41
	(0.12)	(0.46)
Objective Rating	-0.08	0.10
	(0.04)	(0.11)
Subjective Rating * High Level	-0.74	-0.99
	(0.24)	(0.32)
Objective Rating * High Level	0.27	0.41
	(0.06)	(0.08)
Subjective Rating * High Level * Tenure	0.69	0.86
	(0.41)	(0.53)
Objective Rating * High Level * Tenure	-0.25	-0.15
	(0.09)	(0.12)
Subjective Rating * Tenure	-0.23	-0.26
	(0.12)	(0.33)
Objective Rating * Tenure	0.09	0.01
	(0.06)	(0.07)
Powers of Rule Variables and their interactions with Objective and Subjective Ratings.		Yes
Loan Officer Fixed Effects and their interactions with Objective and Subjective Ratings		Yes
No. of Obs.	424	424
Adj R-sq / Pseudo R-sq	0.24	0.48

APPENDIX A
OBJECTIVE INFORMATION DECOMPOSITION VARIABLES

Objective Information Variable	Mean	SD	Min.	Max.	Obs.
Ratio Values					
Pre-tax Interest Coverage (dec.)	-2.05	91.12	-1316.00	284.11	424
Pre-tax Funds Flow Interest Coverage (dec.)	2.49	81.70	-1254.50	322.87	424
Funds from operations/Total Debt (%)	13.68	49.38	-27.74	700.00	424
Free Oper Cash Flow/Total Debt %	15.19	204.09	-21.59	4100.00	424
Pre-Tax Return on Avg Capital %	0.23	2.99	-30.29	23.25	424
Total Debt / Capitalization %	0.39	0.83	-14.27	4.71	424
Current Ratio (dec.)	1.37	1.32	0.00	13.42	424
Ratio Scores (0-22)					
Pre-tax Interest Coverage	11.00	7.99	0	22	424
Pre-tax Funds Flow Interest Coverage	11.38	7.68	0	22	424
Funds from operations/Total Debt (%)	10.25	7.85	0	22	424
Free Oper Cash Flow/Total Debt	10.22	8.69	0	22	424
Pre-Tax Return on Avg Capital %	9.42	8.67	0	22	424
Total Debt / Capitalization %	14.24	6.21	0	22	424
Current Ratio	7.04	5.88	0	22	424
Implied Ratings (1-7)					
Pre-tax Interest Coverage	4.46	2.54	1	8	424
Pre-tax Funds Flow Interest Coverage	4.57	2.47	1	8	424
Funds from operations/Total Debt (%)	4.19	2.52	1	8	424
Free Oper Cash Flow/Total Debt	4.27	2.73	1	8	424
Pre-Tax Return on Avg Capital %	3.97	2.76	1	8	424
Total Debt / Capitalization %	5.39	2.08	1	8	424
Current Ratio	3.16	1.85	1	8	424
Rating Score	10.49	5.58	0	21	424
Financial Rating	4.19	1.67	1	8	424
Size Test	2.30	1.44	1	6	424

APPENDIX B
SUBJECTIVE INFORMATION DECOMPOSITION VARIABLES

Subjective Information Variable	Mean	SD	Min.	Max.	Obs.
Industry Risk Assessment					
Trend in Output	3.51	0.80	1	7	424
Trend in Earnings	3.27	0.78	1	7	424
Cyclicality	3.35	0.81	1	7	424
External Risks	3.53	0.71	2	5	424
Competitive Position					
Market Position	4.28	1.47	1	7	424
Product Line Diversity	3.88	1.12	1	7	424
Operating Cost Advantage	3.46	0.89	1	7	424
Technology Advantage	3.70	0.92	1	7	424
Key Success Factors	3.67	0.84	1	7	424
Management					
Professionalism	3.67	0.90	1	7	424
Systems and Controls	3.66	0.89	1	7	424
Financial Disclosure	3.72	0.85	1	7	424
Ability to Act Decisively	3.77	0.80	1	7	424
Risk Management Policies					
Leverage Policy	3.34	0.85	1	7	424
Liquidity Policy	3.36	0.86	1	7	424
Hedging Policy	3.60	0.86	1	7	424
Access to Capital					
Capital Markets	3.47	1.11	1	7	424
Banks	3.77	1.01	1	7	424
Overall Business Ratings	3.47	0.66	1	5	424