Estimating The Effect Of Hierarchies On Information Use

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Preliminary Draft

January 2006

Abstract

We estimate the effect of credit approval at higher hierarchical levels on the usage of soft and hard information. Credit approved at higher levels (that are more distant from the source of information generation) relies more on hard information content and less on soft information content. Since the assignment of firms to approval levels is determined by rules based on objective criteria, we use regression discontinuity techniques to address endogenous firm selection concerns. We also use loan officer fixed effects to guarantee that our results are not driven by differences in the source of information across approval levels. The decrease in soft information sensitivity and the increase in hard information sensitivity at higher levels is not gradual but happens suddenly in between levels where officers sit in different geographical locations. The drop in soft information sensitivity is more pronounced for more subjective soft information variables, and the drop is smaller when the source of information is more experienced loan officers. Our results highlight the importance of organizational design for a firm's ability to use soft information, and point to a loss of informativeness when soft information is conveyed within large hierarchies.

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One of the most striking changes in our economic landscape over the last century has been the evolution of firms from family businesses into large hierarchical organizations. This dramatic rise of *corporations* as major players in economic activity has led to the development of organizational theory as a new discipline within economics. A key question in this literature concerns the trade-offs that corporations face when designing the size and scope of their organization. For example sub-dividing tasks across agents arranged within a hierarchy can increase productivity due to specialization of tasks, but can also lead to higher communication costs as the size of a hierarchy expands.

The exact nature of such trade-offs determines not only the efficient design and size of organizations, but also the type of activities that large organizations are better able to perform. One of the main costs of large hierarchical organizations emphasized in theory is costly communication, particularly that of soft information. For example, Aghion and Tirole (1997) and Stein (2002) argue that when agents responsible for collecting information do not have decision making authority and instead have to communicate their information "upwards", they will have less of an incentive to exert effort in information collection. In fact even if such incentive effects are absent, the very act of communicating subjective information across a large hierarchy can lead to information losses through various channels (see e.g. Bolton and Dewatripont (1994), Radner (1993), Becker and Murphy (1992) and Garicano (2000)).

Despite the theoretical and practical importance of investigating costs and benefits of various organizational designs, empirical work in this area remains rare. This paper evaluates the costs of communication within hierarchies by estimating the effect of upward communication of soft and hard information on their reliability. Our empirical design uses a data set hand-collected from the credit folders of a large multinational bank in Argentina.

There are three basic features of this data set that enable us to test the effect of communication on information reliability. First, it contains both subjective and objective information collected by a loan officer regarding a firm. Subjective information includes grades on intangibles such as "firm reliability" and "management professionalism", while objective information includes audited firm financials. Second, there is significant variation in the hierarchical level within the bank where this information is used to make the final credit approval decision. For example, for some firms the loan officer himself has the authority to use the information he collected and make the credit approval decision without contacting any higher officials. However, for other firms he is required to send the collected information upwards where more senior officials make the final credit approval decision. These differences across firms in who gets to approve their credit generates variation in terms of how far a given piece of information needs to travel. Third, the credit approval level for a firm is determined ex-ante by a set of rules based on some very objective criteria such as size and industry. The variables used by these rules to assign firms to different levels enable us to address some of the endogeneity concerns.

In order to understand how we use our data to compare the costs of communicating soft vs. hard information within an organization, consider a bank with an organizational structure consisting of two hierarchical levels: high and low. The bank has to decide how much to lend to a firm, and this lending decision depends on firm quality. A loan officer sits at the lower level and generates two signals regarding firm quality. The first is a subjective or soft signal concerning "professionalism", while the second is an objective or hard signal consisting of the firm's recent ROA in audited financials. Thus a firm may receive an "A" from the loan officer in professionalism, coupled with a 10% ROA.

The subjective and objective signals are then used to infer firm quality and make the credit approval decision, i.e. how much to lend. When inferring firm quality from the two signals, the decision maker will put more *weight* (in the statistical sense) on the signal with more *informativeness*. The informativeness of a signal is simply a measure of its covariance with the underlying variable of interest, i.e. firm quality in our case.

The noteworthy organizational variation is that the decision maker might be the loan officer *or* his superior. Theories of costly communication suggest that the informativeness of soft information signals declines faster than that of hard information signals when communicated across hierarchical levels. The reasons for this loss of informativeness can be multiple. It could be that the loan officer has less of an incentive to gather good quality information when he is not the decision maker. Alternatively it could be the difficulty in decoding subjective data, or differences in preferences. For example, what does an "A" in professionalism given by someone else really mean? Regardless of the exact reason for costly communication, as long as soft signals lose informativeness quicker, the theory makes a simple prediction: A decision maker at the higher level will put less weight on soft information and more on hard information relative to when the loan officer is also the decision maker.

We can test the above prediction in our data since it records all subjective and objective information collected by the loan officer, as well as the final approval level for a firm and the approved credit amount. However, there are some endogeneity concerns that deserve attention before we can accurately interpret our results. The basic endogeneity concern is that firms allocated to different approval levels might be inherently of different types. For example, suppose that larger and well-established firms are more likely to be sent to higher levels for approval *and* that these are also the firms that intrinsically have less relevant soft information. Then officer at higher levels will put less weight on soft information - even if communication were perfect - because firms assigned to them have naturally low soft information. Another endogeneity story could be that firms that are supposed to be decided by loan officers are sent to better loan officers with better ability to extract quality soft information. In such a scenario, loan officers deciding on credit approvals will put more weight on soft information simply because they are better at generating soft information compared to loan officers who cannot make decisions on their own and have to communicate their low quality soft information to superiors.

We account for such endogeneity concerns in two ways. First, we know the identity of the loan officer collecting information. Hence by appropriately using loan officer fixed effects, we ensure that sensitivity to soft and hard information is compared across levels for firms whose information was collected by the *same* individual. Second, the allocation of firms to different approval levels is based on some pre-specified set of rules outlined in the credit manual. These rules are based on some objective firm characteristics such as firm size and changes in profitability. Moreover by necessity the assignment rules are a discontinuous function of firm characteristics that determine the approval level. We can thus adopt a regression discontinuity framework and control for any endogenous change in information sensitivity driven by the rule assignment variables.

Our results indicate that consistent with the communication costs literature, credit sensitivity to soft information is smaller and sensitivity to hard information is larger for firms approved at higher levels. The loan officer fixed effects coupled with controls for selection rules suggests that we can attribute our findings to a direct effect of communication costs on information use. This interpretation receives further support from evidence that the decline in soft information sensitivity and increase in hard information sensitivity is not gradual. In particular, firms in our sample can be approved in one of five different hierarchical levels within the bank. We find that the decline in soft information sensitivity is sudden and occurs between levels 2 and 3 of the bank. The increase in hard information sensitivity also follows the same pattern and occurs between levels 2 and 3.

These sharp changes in hard and soft information sensitivity are driven by the geographical location of bank officers. Officers at levels 1 and 2 always sit in the same bank branch where the level 1 officer collects all soft and hard information. Level 3 officer on the other hand may or may not sit at the same bank branch as level 1 and 2 officers. We find that the sharp change in credit sensitivity to information occurs at level 3 *only* when the level 3 officer sits at a branch different from that of level 2 officer. If the level 3 officer also sits in the same branch as level 2, then the change in sensitivity occurs at level 4 where the officers always sit outside the loan officers' branches.

If communication costs are driven by the subjectivity of soft information, then one would expect the decline in soft information sensitivity to be greater for more subjective or "softer" pieces of soft information. Decomposing our aggregate measure of soft information into its constituent parts, we find that the decline in soft information sensitivity is larger for soft information variables with greater degree of subjectivity.

We also find that the decrease in sensitivity to soft information is lower when information is generated by more experienced loan officers. This suggests that officers higher up are better able to understand and "decode" soft information from experienced loan officers perhaps as a result of repeated dealings with them.

Overall our results suggest that soft information is more difficult to communicate when the communicating parties sit in different geographical locations. One interpretation of this finding is that conveying subjective information over long distances is difficult using impersonal communication methods such as phone, fax or the internet. Section IV discusses some other channels that can also lead to a costly communication of subjective information across hierarchies. It also presents some further evidence to tease out the various channels.

As outlined earlier, this paper is related to the large body of theoretical literature that studies the costs of information transmission within hierarchies and how these costs determine the size and scope of organizations. There is also a strand of empirical literature that indirectly links communication costs related to soft information to the scope of a firm's business activities. For example, since the pioneering work of Berger and Udell (1995) and Petersen and Rajan (1994 and 2002), relationship lending is thought to be soft information intensive. Consistent with this view, 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 than large banks and foreign banks. Our paper differs from this work in that we look inside the organizational design to directly compute the cost of communicating soft information.

I. Information and Organizational Design

A. Conceptual Framework

A number of papers investigate how organizational design and delegation of authority alters incentives to acquire information and the ability to communicate it within an organization. An important strand of this literature (see Petersen (2004) for a review) differentiates between information based on the ease with which it can be acquired and communicated. It defines hard information as objective information that is easily quantifiable and communicable to a third party. Soft information on the other hand is subjective, personalized and hence difficult to communicate fully.

Using these definitions papers such as Aghion and Tirole (1997) and Stein (2002) show that decentralization of authority enhances incentives to acquire and use soft information. On the other hand hierarchical structures are less conducive for soft information intensive activities and more suitable for hard information related tasks. While these papers emphasize the effect of hierarchies on the incentive to acquire soft information, there are also other explanations for why soft information may be less effective in large organizations. For example, just the very act of communicating subjective or soft information across hierarchies can be costly in terms of information loss (see e.g. Bolton and Dewatripont (1994)).

In this section we develop a simple conceptual framework that incorporates the idea that soft information loses informativeness when used at higher levels within a hierarchy. The loss of informativeness could be due to incentive effects or costs of communication. The purpose of our exercise is to understand the empirical implications of this loss of informativeness. In particular, we want to outline how the loss of informativeness impacts the sensitivity of decision making to *observable* information.

Our framework can be illustrated with the help of Figure I that shows the organizational design of a bank trying to decide how much to lend to a firm. The bank has two layers of hierarchy: a loan officer sits at the lower level and his manager at the higher level. Loan size to any given firm is based on the estimated quality, Q, of that firm. It is the loan officer's responsibility to collect all firm level information that may be used in estimating Q.

The loan officer extracts two types of signals from the firm. An objective (hard) signal H, and a subjective (soft) signal S. The objective signal consists of easily quantifiable information such as size, profitability and other financial ratios. The subjective signal on the other hand is more qualitative and includes information such as management quality and project strength. Since both H and S are positively correlated with Q, they are used to infer the underlying firm quality. Based on this information a final decision is then made on how much to lend to the firm.

Even though the same information, i.e. signals H and S are used to decide how much to lend, the decision can vary depending on who is making the final credit approval. In particular, if the final approval authority rests with the loan officer, he might make a credit decision different from the one a manager would have made. The choice of who makes the final credit approval decision depends on the organizational design of the bank.

If the authority to approve credit is vested in the loan officer then he will be using information he himself collected when making his decision. However, if final approval is made by the manager then he will be using information as communicated to him by the loan officer. For reasons such as information gathering incentives of the loan officer, and communication costs highlighted earlier, the quality of subjective information reaching a manager could be weaker. Therefore in making the same credit approval decision, a manger may give less weight to the soft information signal S and more weight to the hard information signal H, compared to a loan officer.

As an example, suppose that the hard information signal H collected by the loan officer consists of ROA of the firm during the last 3 years, and is recorded as 20% in audited accounts of the firm. Soft information 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 "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 the grade "A" is communicated, it can lose part of its "informativeness" for a number of reasons. First, 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 soft information into grades or scores naturally leads to a loss of content for a person other than the one who actually collected this information. Third, if the 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.

Whatever the reason for poorer soft information at the manager level, the loss of informativeness in soft signals can be easily represented statistically. "Informativeness" of a signal can be defined as its covariance with the main underlying variable of interest. In our case this will be the covariance of H and S with Q, and can be defined as σ^2_{qh} and σ^2_{qs} respectively. A loss in informativeness of the soft signal can be interpreted as a decline in σ^2_{qs} as it travels across hierarchies. We can thus define soft and hard information in terms of their relative loss in informativeness when used across hierarchies:

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

where Δ refers to the loss in covariance of a signal as it is communicated up the hierarchy.

Given the statistical definition of soft and hard 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 estimate the true underlying firm quality Q. He then approves a loan of size $L(Q)$ based on the inferred Q.

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 IV 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^2_q , α^2_h and α^2_s 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, $\beta_H = \frac{\sigma^2_{qh}\sigma^2_s - \sigma^2_{qs}\sigma^2_{sh}}{\sigma^2_h\sigma^2_s - (\sigma^2_{sh})^2}$ and $\beta_S = \frac{\sigma^2_{qs}\sigma^2_h - \sigma^2_{qh}\sigma^2_{sh}}{\sigma^2_h\sigma^2_s - (\sigma^2_{sh})^2}$. 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[1]. The definitions of soft

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

and hard 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 hard information increases while that to soft 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.*

The result above is based on the relative loss in informativeness of hard and soft signals when used across hierarchies. Both loan officer and manager were assumed to be risk neutral in the set up above. The sensitivity differentials between loan officer and manager will be further increased if one takes into account risk aversion. The reason is that loan officers who collect soft 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 soft grade of "A". Thus the soft signal will have a tighter variance for loan officers than managers. Since risk aversion punishes losses more harshly, for a unit increase in reported soft information grade, managers will be more conservative than loan officers in increasing their approved credit.

The change in sensitivity to hard and soft information at higher levels can also result for reasons such as differences in the abilities or objectives of officers at different hierarchical levels. We will discuss this and other factors in more detail in section IV.

B. Empirical Design

It is important to realize that Proposition I is empirically testable since signals $\widehat{H}$ and $\widehat{S}$ are observable to the econometrician as well as the ultimate decision maker. For example, theory predicts that if a firm has soft 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. We can thus test proposition 1 by estimating an equation of the form:

$$L = \alpha + \beta_H * H + \beta_H^M * (H * MGR) + \beta_S * S + \beta_S^M * (S * MGR) + \varepsilon \tag{3}$$

where L is log of approved credit and MGR is an indicator variable for whether a loan 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.

We estimate (3) using a data set containing detailed records of all objective and subjective information collected by loan officers in a given bank. The data also includes informations on final approved credit and whether discretion to approve this credit rests with the loan officer or someone higher up in management. The data is described in more detail in the next section.

In order to properly identify (3) coefficients β_H^M and β_S^M should only include the direct effect of approval level on credit sensitivity. There is a concern however that spurious factors might influence these coefficients as well, making their interpretation subject to ambiguity. One can separate these into concerns driven by *firm selection*, and concerns driven by *loan officer selection*.

The *firm selection* concern is that firms sent to higher levels for approval may be very different types of firms. For example, suppose that firms with less reliable soft 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 soft information. In such a scenario even if there is no loss of soft information across hierarchies, managers will put less weight on soft information compared to loan officers since their firms have poorer quality soft information to begin with. Alternatively if firms with better hard 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 hard relative to soft information even if there is no loss of informativeness in communicating subjective information.

The *loan officer selection* concern is that firms approved at different levels might be systematically given to different types of loan officers. Since information for all types of firms is collected by the loan officers, it might be the case that firms being approved by loan officers themselves are given to loan officers with better ability and expertise. In such a scenario, information regarding firms sent to higher level officers for approval will be collected by less able or inexperienced loan officers. Consequently a lower sensitivity to soft information at higher levels may be an artifact of systematic differences in the ability of loan officers rather than a direct impact of higher approval level.

The firm selection concern is quite difficult to address in general since the assignment of firms to different approval levels might be based on unobserved firm characteristics. Fortunately this is not the case in our sample. The multinational bank where our data comes from outlines detailed "rules" in its credit manual on the allocation of firms to different levels. Importantly these rules are based on hard, objective, and measurable firm characteristics such as size, industry, loan structure, and so on. These rules are also tightly followed (something we can cross-check). Since we know the firm characteristics that go into the selection equation of assigning firms to approval levels, we can control for firm selection concerns by including these rule variables and their interactions with H and S on the right hand side of (3).

We address the loan officer selection concern by including loan officer fixed effects, and also 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.

Let Z denote rule variables assigning firms to approval levels, and α_i the loan officer fixed effect. Then we can account for firm selection and loan officer selection concerns by updating (3) to[2]:

$$L = \beta_H^M * (H * MGR) + \beta_S^M * (S * MGR) + \beta_1 Z + \beta_2 (H * Z) + \beta_3 (S * Z) + \alpha_i + (\alpha_i * H) + (\alpha_i * S) + \varepsilon \quad (4)$$

We can also include higher powers of Z (such as Z^2) and their interactions with H and S in (4) to allow greater functional form flexibility for firm selection controls. The inclusion of linear and quadratic firm selection criteria 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. Furthermore, given the loan officer fixed effects and their interactions in (4), our coefficients cannot be influenced by loan officer selection concerns.

Regression discontinuity design was first introduced in labor economics and has been used in a number of influential studies such as van der Klaauw (1996), Angrist and Lavy (1999), and Angrist and Krueger (1999). The idea behind this technique is to include continuous linear and non-linear functions of the approval selection variables as controls. The controls enable the estimating equation to isolate "jumps" in the approval level mapping functions. These jumps are then used to estimate

[2] We do not have to put in $(\alpha + \beta_H * H + \beta_S * S)$ in the equation anymore since loan level fixed effects and their interactions with H and S completely absorb these terms.

the direct impact of approval level on information sensitivity. The discontinuity approach solves endogeneity concerns since there is no reason to believe that firm attributes affecting information use through other channels will also have an effect that "jumps" at exactly the same points as the approval level mapping function.

The intuition behind discontinuity design can be understood through a simple example. Suppose the approval level for a firm is determined using a single variable Z, say size. There is a particular 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 II shows the function mapping Z to approval level. Given that larger firms are sent to higher level for approval, there might be an endogeneity concern in estimating (3) if soft information is less relevant for larger firms. For example, perhaps the informativeness of soft information (σ^2_{qs}) is lower for larger firms. If this were the case then β^M_S would be biased downwards and one might get a significant and negative coefficient even if soft information were communicated to the manager without any loss of informativeness.

More generally the identification concern is that selection variable Z might be correlated with the original quality of hard or soft information (i.e. σ^2_{qh} and σ^2_{qs}). Figure II plots some possible relationships between Z and σ^2_{qs}, and Z and σ^2_{qh} that can bias β^M_S downwards and β^M_H upwards respectively. Since proposition 1 predicts a negative β^M_S and positive β^M_H, any bias of the form displayed in Figure II makes it impossible to test the proposition. A regression discontinuity design solves this problem by observing that the relationship between Z and approval levels experiences a sharp discontinuity and jump at $\overline{Z}$, while there is no reason to believe that the relationship between Z and σ^2_{qs} or Z and σ^2_{qh} also jumps at exactly the same point. Moreover the concern that Z and σ^2_{qs} might be negatively correlated (as in plot A in figure II), or that Z and σ^2_{qh} might be positively correlated (as in plot B in figure II) is addressed by including flexible functions of Z, $(Z * S)$ and $(Z * H)$ as controls. A rough explanation of discontinuity design is that it compares two firms $\overline{Z}^+$ and $\overline{Z}^-$ that are almost identical with respect to selection criteria but differ in their approval level.

It is important for discontinuity design that the selection variables that assign firms to approval levels are objective variables that cannot be influenced by the subjectivity of a loan officer. If assignment of firms to levels were based on subjective criteria, then one would not really know which rule variable to use in discontinuity design. However all selection variables in our sample are pre-determined by objective firm attributes such as size and changes in firm financial ratios.

When we take regression discontinuity approach to actual data, it turns out that there is not one but several selection variables. Furthermore assignment rule contained in the bank's manuals is a complicated discontinuous function of these rule variables. Thus our actual empirical specification exploits discontinuities in the entire data distribution as opposed to only one point in figure II.

II. Data Description

We personally conducted field work in the bank in the months of July and December of 2004 to collect our data. The hierarchical structure analysis corresponds to the year 1998. There are several reasons for choosing this year. First, as explored in Liberti (2003) 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 which could jeopardize the results if using 1999. Second, 1998 was a positive year for Argentina in terms of macro-economic activity. Third, we managed to hand-collect and assemble the data for *all* of the corporate clients which the bank has an outstanding relationship with.

We were granted access to the credit folders of all 424 corporate clients of a large multinational bank in Argentina. A firm is classified as corporate by the bank if its annual net sales exceed $50 million pesos[3]. The credit folders contain *every* information collected by the bank about a given firm from the time of credit application till the time of credit approval. The content, type and quality of information is *consistent* across the credit folders. All credit folders contain the same type of information. Using these folders we construct a database containing all objective and subjective pieces of information collected by a loan officer, the hierarchical level of the bank at which credit has to be approved, the ex-ante selection variables that determine this level of approval, and the final approved credit line. These variables are described in detail below.

[3] 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.

A. Approval Level Rule Variables

When 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.

The hierarchical design of the bank is summarized in Figure III. It consists of 5 levels of approval, where 1 is the lowest and 5 the highest. The loan officer sits at level 1. A credit file must travel sequentially through all levels until it reaches the highest level of approval for that firm. The officer authorized by the credit rules then makes a final decision on how much to lend to a firm.

Table I shows that 26.6% of loans[4] are approved at level 1 by loan officer himself. Another 37.4% are approved at level 2, and the remaining are approximately equally divided among levels 3, 4 and 5. Table I also shows the summary statistics for rule variables that base mapping function used to assign approval levels to firms. 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. None of these variables are subjective or based on the discretion of the loan officer. This is important for satisfying the discontinuity design identifying assumption as discussed in section II.

B. Informational Variables

Once a credit application is filed and the ultimate approval level is known, its 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 loan officer manages around 20-25 firms (on average) that are mostly clustered in a single or related industries.

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 "hard" if it consists of objective and quantifiable measures that are easy to collect, store, and transmit. Hard variables can also be verified by a third party at little cost. Such variables include audited firm financials such as net-worth, size, interest coverage and return on assets. The bank also summarizes these hard variables into an overall "hard

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

risk rating" index and two sub-indices. 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 hard information variables as well as the two indices constructed by the bank using these variables. Appendix A provides a full description of the hard variables used by the bank in coming up with the financial risk rating and size rating.

The second category of informational variables collected by the loan officer are soft variables. These are characteristics that are subjective, impersonal, difficult to transmit and costly to verify by a third party. The full set of soft information variables 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. Soft variables are recorded on a subjective scale of 1 through 7 by the loan officer, and their full detail is given in appendix B. The numerical categories are arranged in such a way that larger numbers signify better firm quality. The bank also aggregates its soft information into an index of overall business assessment that we will refer to as "soft rating".

Table I provides summary statistics for all soft information variables. Although these variables are all classified as soft, they differ in the degree of their subjectivity or "softness". For example, when a loan officer is asked to report on a firm's ability to access outside funds, he may use some hard 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 softness in the results section.

C. Approved Credit

Once a loan officer collects all required information, credit is approved and authorized by the loan officer himself if he has the authority or 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. The choice of year is suitable since 1998 was stable year for Argentina in terms of aggregate macro-economic activity. However, if a credit application were rejected by the bank, we do not have it in our data.

III. Results

A. Approval Level Rules

We document the relationship between approval level and ex-ante rule variables determining the level. The purpose is to identify the discontinuities that arise in the level assignment process. All variables used by the level assignment rules are objective variables not susceptible to subjectivity or interpretation of the loan officer. If the determination of approval levels were heavily influenced by subjectivity of the loan officer, then it would have been impossible to use a discontinuity approach for identifying the effect of approval levels. An involvement of subjectivity would have made it impossible to know the real reason firms are assigned different levels.

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 firms 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, covenant violations in past, and sharp industry changes can trigger a firm to be sent to higher levels for approval even if it falls in a lower level according to size. It is thus a combination of many discontinuous 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 larger firms 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 with sharp changes in profitability and leverage, risk downgrades in capital markets, covenant violations, negative credit registry report, and firms in volatile markets 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 complex loans such as those of troubled firms or firms experiencing rapid changes.

In all these criteria used to assign approval level to firms, the bank has to decide exact cut off points that send firms to higher or lower approval levels. This necessity of the bank creates several discontinuities in the mapping of rule variables to approval levels. Moreover due to many factors incorporated by the bank in this mapping, discontinuities exist in the entire data distribution. The prevalence of discontinuities allows us to exploit more of the data in estimating credit sensitivity coefficients[5].

Table II also includes some descriptive statistics for the approval process associated with each level. As a credit file goes higher for approval, greater number of officers sign off on the file. It also takes longer to prepare the credit folders of firms sent higher for approval as these firms are likely to have bigger more complex structures and loan requirements. Similarly, firms sent higher up for approval take longer for their application to get processed and approved. It is also more likely for firms at higher approval levels to be sent back to the loan officer for clarification of information, or to be contacted again by the bank.

Discontinuities built into assignment rules can be visualized by regressing approval level on linear and non-linear - but continuous - functions of rule variables. Column (1) of Table III puts in linear functions of the rule variables, and reaffirms that larger firms, troubled firms, and firms experiencing sharp changes are more likely to be sent to higher levels for approval. R-sq is only 0.46 and discontinuities in rule assignment are likely to be responsible for most of the unexplained variation. Column (2) also includes all pair-wise interactions of rule variables but R-sq does not increase much. The sharp non-linearities or discontinuities inherent in rule assignments can further be seen by column (3) that incorporates non-linear functions of the rule variables as well. Despite including functions of powers 1 and 2, adjusted R-sq is only 0.54. Column (4) shows that the top 5 variables in terms of significance

[5] One cannot take this argument too far since an infinitely discontinuous function starts to mimic a continuous function. However with limited variables in the mapping rule, too much discontinuity should not be a concern.

account for almost all of the explained variation 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) as well. However, even with such non-normal estimation techniques pseudo R-sq is not very high.

Results in Table III highlight the many discontinuities inherent in the assignment rules of credit manual. It is the variation in approval levels caused by these discontinuities that we will use to identify the direct effect of approval levels on credit sensitivity to information. Figure IV plots the density of residuals obtained from column (2) in Table III that provided the best fit with continuous functions of the rule variables. Standard deviation of residual in Figure IV is 0.88 compared to a standard deviation of 1.28 for the original approval level. Thus there is significant variation left after taking out continuous functions of the assignment rule variables.

Although the assignment of approval levels is made on pre-existing rules described in credit manuals, on very rare occasions a superior officer might overrule the assignment. Such subjective overturns of the assignment rules is problematic for our identification strategy. However the banks report that this only happens in one or two firms out of our sample of 425 and is unlikely to effect our overall estimates.

The results on Table III 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, that is, they engage in "management by exception". The setting under analysis looks, a priori, very much like the one predicted in the theory.[6]

B. *Approval Level and Credit Sensitivity to Information*

We collapse the 5 approval levels into "high" and "low" around the median to test whether sensitivity of credit to soft and hard information varies by approval level. Approval levels 1 and 2 are classified 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. The results indicate that

[6] Problems, in this case credit folders, flow from below, and advance to a particular layer. They flow recursively, that is they do not get allocated horizontally to one particualr manager but flow upwards. A particular credit generates a whole set of problems that have to be diagnosed and solved for production to take place –here for the credit approval to be completed. As the credit is diagnosed it is assigned a particular hierarchy that will deal with it. However, our main analysis is looking at the impact of approval levels on information use and not for the reasons of hierarchy designs. Garicano (2000) refers to the reasons of the emergence of hierarchies, while our focus is on the flow of information across the hierarchy.

sensitivity of credit approval to soft information dramatically goes down for loans approved higher up in the hierarchy, while sensitivity to hard information increases for loans approved at the high level. However as section I explained, this result might be driven by the endogenous selection of firms with low soft information into higher levels. Column (2) onwards estimate the direct impact of approval levels on information sensitivity in equation (4) by including linear and non-linear functions of the assignment rule variables and their interactions with hard and soft variables. Column (2) puts in linear functions, while column (4) includes linear as well as functions of power 2 of the rule variables as controls. Our coefficients of interest remain qualitatively unchanged in the discontinuity design specifications as well. Thus the increase in hard information sensitivity and decrease in soft information sensitivity at higher levels is likely to be a direct effect of higher approval levels.

The increase in sensitivity to hard information is very similar in magnitude to the drop in sensitivity to soft information at high levels. Even though the coefficient magnitudes are -0.66 vs. 0.23 in column (4), recall that soft rating is measured on a scale of 1-7 while hard rating has a scale of 1-14. Thus the 0.23 coefficient increase in hard should be multiplied by 2 before comparison with the drop of 0.66 in sensitivity to soft information.

Although the discontinuity design in column (4) addresses the endogeneity concern to a large extent, we can further isolate the exogenous variation in approval levels by completely accounting for the source that generates information. This is done in column (5) that includes loan-officer fixed effects and also interacts these fixed effects with hard and soft ratings. The fixed effects approach controls for the person generating soft and hard information in a non-parametric fashion. It thus only explores variation in the level of approval for firms whose credit folders were put together by the *same* loan officer. In other words, with the fixed effects approach one does not have to worry about whether the results are driven by differences in the quality of information collection across firms and we can perfectly control for who is generating the information. Therefore, with this approach we only focus on where the information is used. There are a total of 26 loan officers collecting information for the 424 firms in our sample. Column (5) shows that our main results are completely robust to the fixed effects specification.

Columns (6) and (7) repeat the regressions of columns (2) and (4), but compare sensitivities across all the five levels separately. Results show that credit sensitivity to soft information does not decline between levels 1 and 2, but then declines sharply for level 3. This decline persists for levels 4 and 5 but there is no further deterioration in sensitivity to soft information. Interestingly credit sensitivity for hard information mirrors that of soft information. Hard information sensitivity does not change between levels 1 and 2, but then sharply increases for level 3 and maintains this high sensitivity at levels 4 and 5 as well.

The geographical location of officers at different levels offers a possible explanation for why the drop in credit sensitivity to soft information and the increase in credit sensitivity to hard information occur between levels 2 and 3. Our data includes information on the location of each officer involved in the loan process. The location data shows that the loan officer (who sits 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 hard and soft information among level 1 and level 2 approvals, our results indicate that communicating soft 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. 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 geographical location test.

Table VI B performs this test by interacting hard and soft risk ratings within level 3 firms with a location dummy for the approving loan officer. Even though the number of observations is much smaller, results 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 soft information is much higher than a level 3 officer that sits outside the loan officer's branch. Similarly, sensitivity to hard information increases when the officer sits outside the branch of the loan officer.

Table VI A also compares some 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.

C. Decomposing Information

We have been using hard and soft indices constructed by the bank itself to measure credit sensitivity. However. since we also know the primary variables used to construct these indices, we can check for robustness of results to different ways of aggregating the primary information variables. We first explore the variation in soft information primary variables. Appendix B provided details of all the soft information variables used to construct soft information rating. There are a total of 18 primary soft information variables, divided across five soft information categories. The bank uses its own formula to weight these 18 variables in coming up with an overall soft 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 soft information rank. (i) AVGSOFT: This is a simple arithmetic mean of all the 18 soft information variables, and (ii) WAVGSOFT: This weighs the five categories equally while giving equal weights to the primary soft information variables within each category. Columns (1) and (2) in Table VII repeat the primary regression specification but replace soft information rating with AVGSOFT and WAVGSOFT respectively. The result on credit sensitivity to soft information are very similar in spirit to what we found earlier. As such our main result is not sensitive to the definition of how soft information index is constructed.

Soft information variables also differ in their "softness" or the extent of subjectivity involved in computing them. If sensitivity to soft information declines as a result of communication losses across hierarchies then one would expect such losses to be greater for softer and more subjective soft variables. We therefore divide soft variables according to the degree of subjectivity involved in computing them. The bank creates soft information variables in five categories: industry outlook, risk management policies, access to capital, competitiveness, and management quality. Columns (3) through (7) put these five soft 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 soft 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 soft categories does decline. The three categories that do not decline are also categories that are relatively "less soft". 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 soft. 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 soft information variables into less and more soft categories and test whether the drop in credit sensitivity to soft information at higher approval levels is more pronounced for the softer category of 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 hard information index. As explained earlier, the bank uses seven different financial ratios to arrive at its hard information rating that we have so far used in our analysis. We also constructed our own index of hard information by taking the arithmetic mean of these financial ratios. Results with our index of hard information are qualitatively very similar to those obtained with the bank's hard risk rating (regression not shown).

D. *Does Loan Officer's Experience Matter?*

If the decline in soft information sensitivity at high levels is driven by loss of communication from loan officer up, 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 soft 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. To test if the experience of a loan officer helps facilitate soft information communication, we use our loan officer fixed effects specification and then triple interact soft and hard information sensitivities with loan officers' experience. The results in Table IX show that the decline in soft information sensitivity is much smaller for more experienced loan officers.

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

IV. Discussion of Results

Results in section III can be attributed to the direct effect of higher approval levels on credit sensitivity to information. The regression discontinuity approach makes it unlikely that results were due to spurious correlations generated by the endogenous assignment of firms to approval levels. Moreover, sensitivity to information does not vary linearly with approval levels but rather jumps at that approval level where an officer goes out of the local bank branch. This lends further support to the view that we are capturing a direct effect of where a credit folder has to travel to get approval. Our results therefore indicate that organizational design matters in effecting the use of information within an organization.

Level of approval may effect sensitivity to information through a number of channels. The interpretation of our results can vary depending on the channel responsible for the estimated differences in credit sensitivity. We discuss the possible channels below. It is useful to keep in mind that these interpretations are not mutually exclusive and our results may be driven by more than one interpretation.

A. Loss in Communication

An obvious interpretation of our results is the theory based on costly communication of soft information outlined in section I. All our results support such an explanation. Not only does credit sensitivity to soft information decline at higher levels, but the decline is larger for more subjective information. Similarly the drop in sensitivity only kicks in when an officer in the higher hierarchy is located in a different branch. This is further confirmation of the view that loss in informativeness of soft information is driving the results. 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. It is also harder for people to communicate in person when they are separated by geographical distance. 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.

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 incentives explanation is more likely to effect soft information acquisition since it is this type of information that is likely to require most effort and thinking on part of the loan officer. However, for an incentive based story to explain all of our results, we have 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 hard information is difficult to manipulate due to its objective nature, manipulation is easier with soft 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 soft information as they know the information has been tempered with.

However strategic manipulation is unlikely to be the main explanation for 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 soft 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 hard and soft information variables. Alternatively officers at different levels may have different tastes or objectives in terms of incorporating hard and soft 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 soft 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.

V. Concluding Remarks

We estimate the effect of credit approval at higher hierarchical levels on the usage of soft and hard information. Credit approved at higher levels (that are more distant from the source of information generation) relies more on hard information content and less on soft information content. Since the assignment of firms to approval levels is determined by rules based on objective criteria, we use regression discontinuity techniques to address endogenous firm selection concerns. We also use loan officer fixed effects to guarantee that our results are not driven by differences in the source of information across approval levels. The decrease in soft information sensitivity and the increase in hard information sensitivity at higher levels is not gradual but happens suddenly in between levels where officers sit in different geographical locations. The drop in soft information sensitivity is more pronounced for more subjective soft information variables, and the drop is smaller when the source of information is more experienced loan officers. Our results highlight the importance of organizational design for a firm's ability to use soft information, and point to a loss of informativeness when soft information is conveyed within large hierarchies.

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Figure I: An Example of Bank Hierarchical Structure

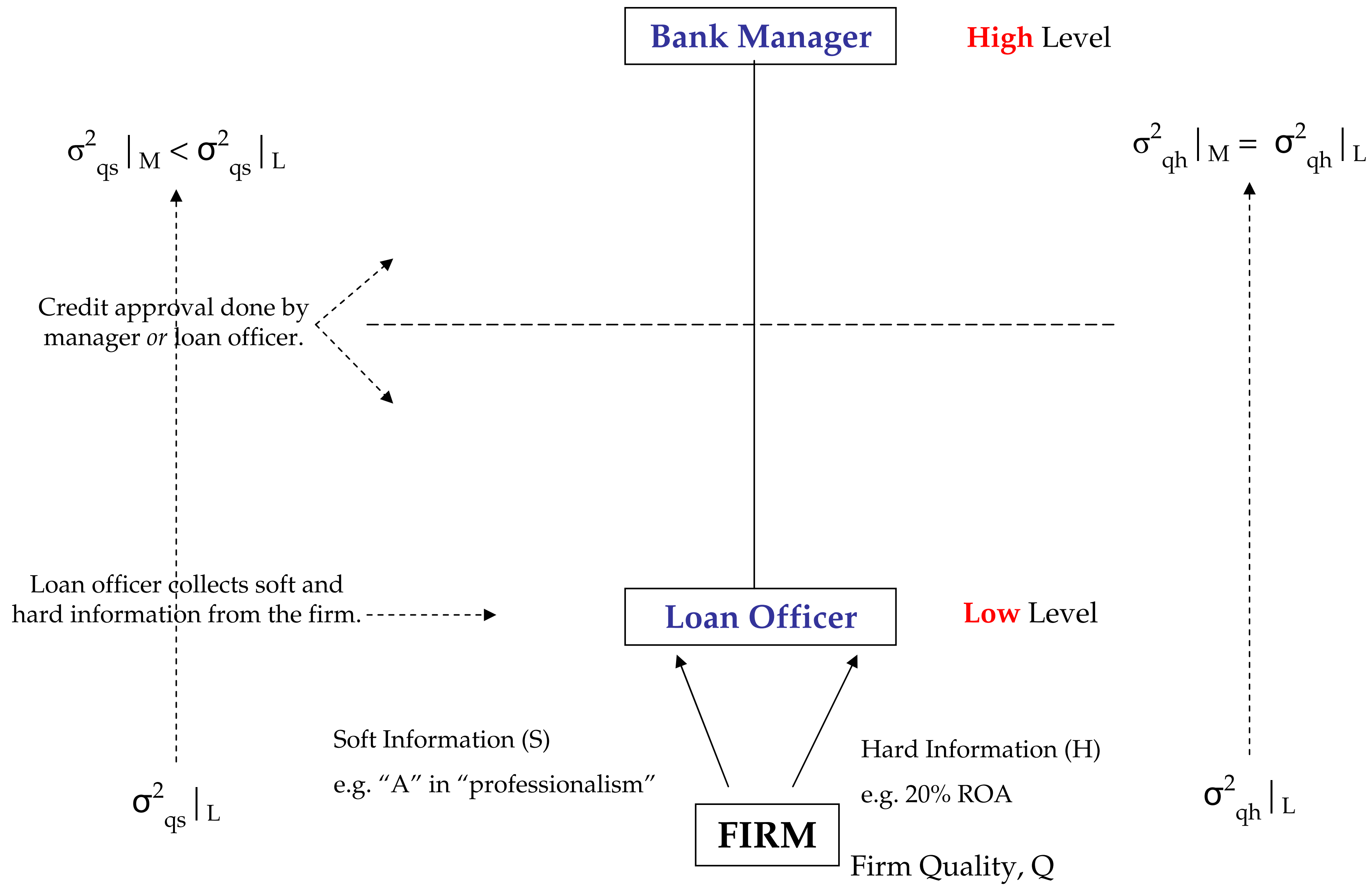


Figure II: Empirical Strategy

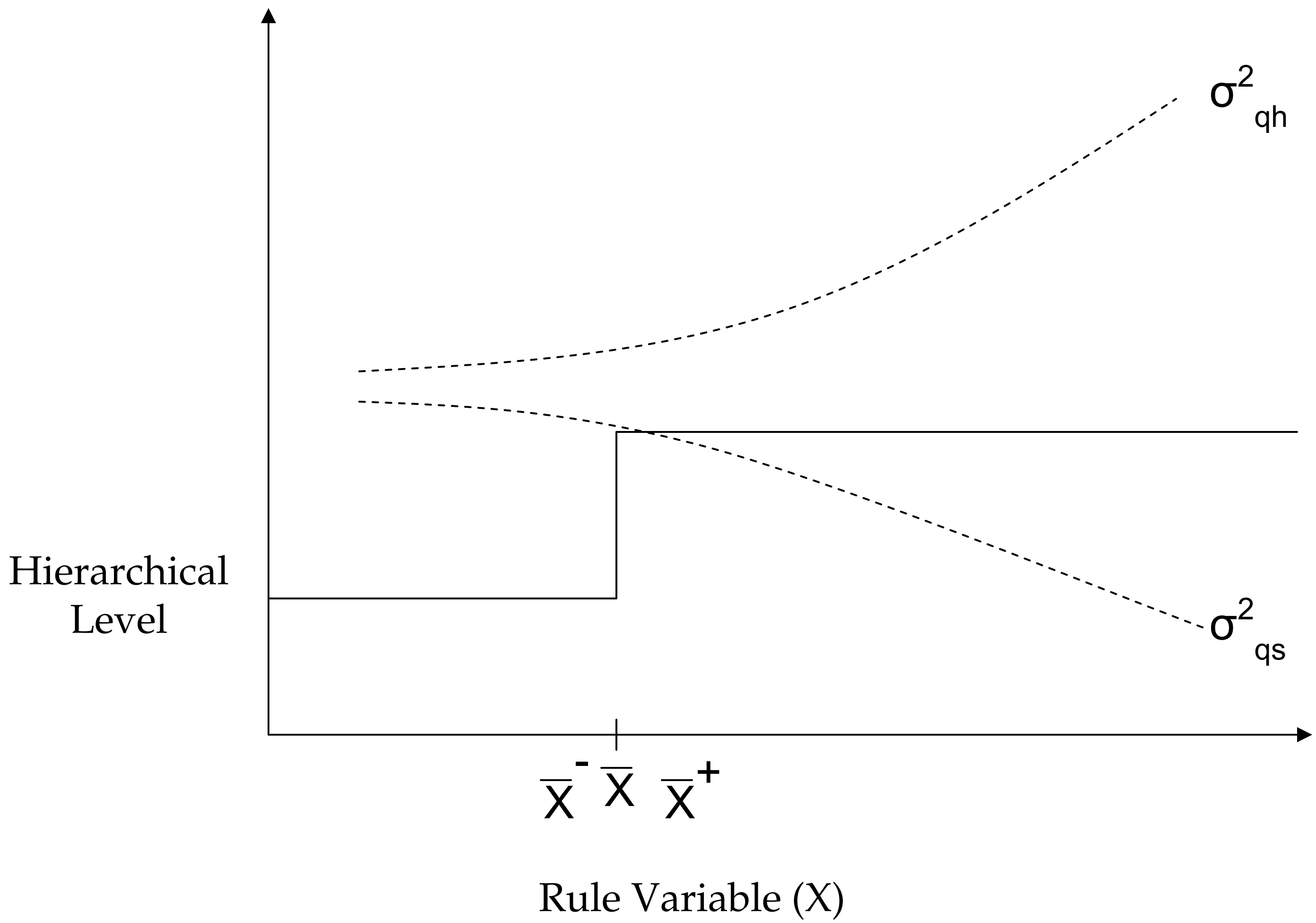
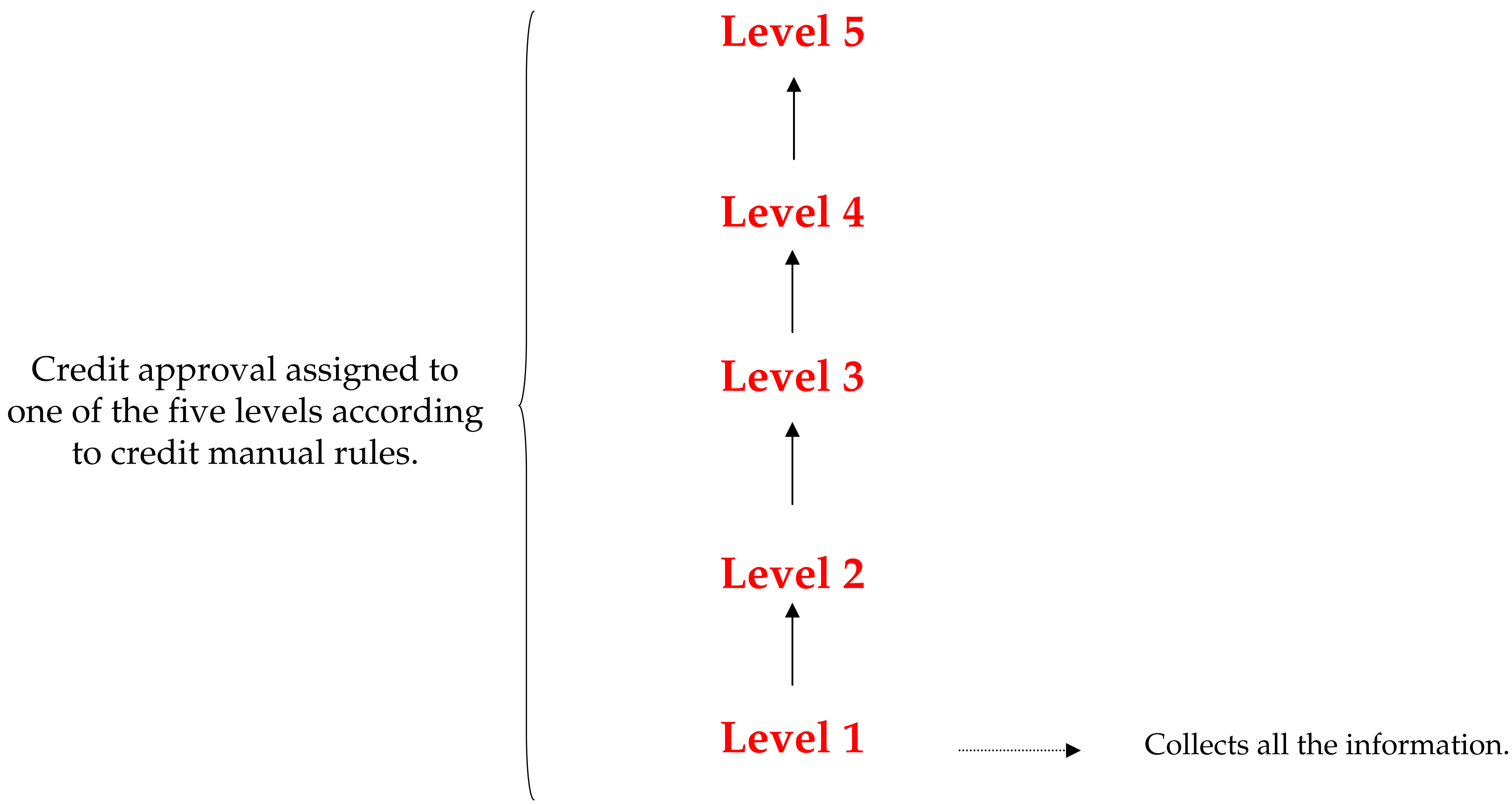
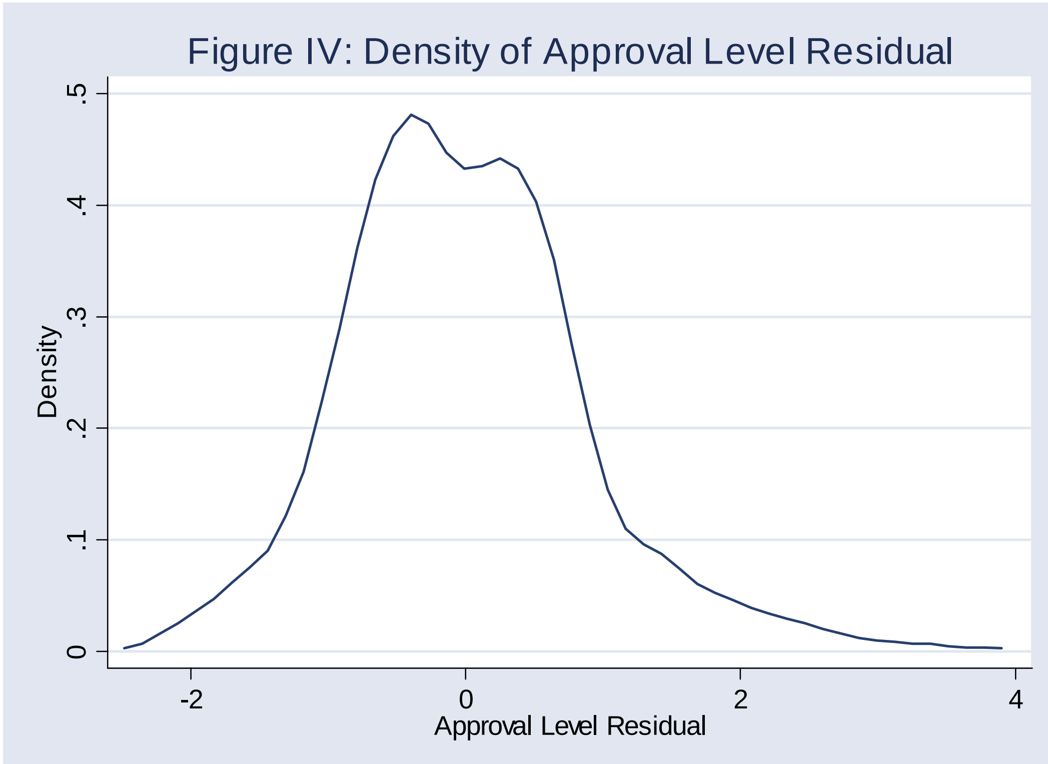


Figure III: Institutional Setup: Hierarchical Decision-Making Process





Standard Deviation of Approval Level = 1.28
Standard Deviation of Residual = 0.88

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
Organizational Structure Variables					
Number of Approval Signatures	2.21	1.12	1.00	6.00	424
Time To Prepare Credit Folder (days)	11.70	15.08	0.00	63.00	424
Time To Approve Credit (days)	24.10	39.42	1.00	168.00	424
Revise and Resubmit Case	0.17	0.38	0.00	1.00	424
Extra Client Information Requested	0.44	0.50	0.00	1.00	424
Approval Level Rule Variables					
Facility Risk Rating (FRR)	12.39	4.15	1.00	22.00	424
Internal Classification Code	1.20	0.59	1.00	4.00	424
Maturity of Loans > 3 Years (%)	0.14	0.30	0.00	1.00	424
Unsecured Loans (%)	0.71	0.44	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
Amount Over Maximum Limit	0.00	0.05	0.00	1.00	424
Downgrade in FRR Since Last Review	0.04	0.20	0.00	1.00	424
Significant Increase in Total Facilities	0.02	0.13	0.00	1.00	424
Adverse Change in Country/Outlook	0.06	0.24	0.00	1.00	424
Risk Event at the Company	0.02	0.14	0.00	1.00	424
Adverse Change in Risk Profile	0.00	0.05	0.00	1.00	424
Adverse Change Critical Success Factors	0.00	0.05	0.00	1.00	424
Covenant Violations	0.02	0.13	0.00	1.00	424
Qualified Auditors' Opinion	0.01	0.10	0.00	1.00	424
Family Company?	0.16	0.37	0.00	1.00	424
Override in Credit Model	0.03	0.17	0.00	1.00	424
Net Worth (logs)	9.93	2.78	0.00	15.79	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

TABLE I (Continued)
SUMMARY STATISTICS

Variable	Mean	SD	Min.	Max.	Obs.
Hard Information Variables					
Pre-tax Intererst Coverage	-2.05	91.12	-1316.00	284.11	405
Pre-tax Funds Flow Intererst Coverage	2.49	81.70	-1254.50	322.87	405
Funds from Operations/Total Debt (%)	13.68	49.38	-27.74	700.00	405
Free Oper. Cash Flows/Total Debt (%)	15.19	204.09	-21.59	4100.00	405
Pre-tax Return on Average Credit (%)	0.23	2.99	-30.29	23.25	405
Total Debt/Capitalization (%)	0.39	0.83	-14.27	4.71	405
Current Ratio	1.37	1.32	0.00	13.42	405
Size Rating	2.30	1.44	1.00	6.00	405
Financial Risk Rating	9.62	4.97	1.00	20.00	405
Hard Risk Rating [1-7]	2.89	0.89	1.00	7.00	424
Hard Risk Rating [1-14]	6.75	2.53	1.00	14.00	424
Soft Information Variables [1-7]					
Industry Position	3.41	0.59	1.75	5.00	409
Competitive Position	3.80	0.81	1.00	6.60	409
Management Quality	3.70	0.75	1.00	6.50	409
Risk Management Policies	3.43	0.71	1.00	6.33	409
Access to Capital	3.62	0.98	1.00	7.00	409
Average Soft Risk Rating	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

Variable	Mean Level 1	Level 2	Level 3	Level 4	Level 5
Organizational Structure Variables					
Number of Approval Signatures	1.00***	1.96***	2.61***	3.07***	4.64
Time To Prepare Credit Folder (days)	3.51***	5.95***	18.59*	21.18***	33.19
Time To Approve Credit (days)	1.35***	6.03***	23.98***	59.26***	104.91
Revise and Resubmit Case	0.03	0.06***	0.28***	0.56**	0.36
Extra Client Information Requested	0.51	0.52	0.39***	0.16**	0.38
Approval Level Rule Variables					
Facility Risk Rating (FRR)	9.61***	11.89***	14.37	14.43***	16.40
Internal Classification Code	1.06	1.09***	1.24	1.23***	1.88
Maturity of Loans > 3 Years (%)	0.06**	0.10**	0.24	0.22	0.22
Unsecured Loans (%)	0.76	0.78***	0.56	0.61	0.67
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
Amount Over Maximum Limit	0.00	0.00*	0.02	0.00	0.00
Downgrade in FRR Since Last Review	0.01	0.01***	0.11	0.12	0.05
Significant Increase in Total Facilities	0.00	0.00***	0.07**	0.00**	0.07
Adverse Change in Country/Outlook	0.04	0.02***	0.24**	0.09*	0.00
Risk Event at the Company	0.00	0.01	0.02	0.02**	0.12
Adverse Change in Risk Profile	0.00	0.00	0.00	0.00	0.02
Adverse Change Critical Success Factors	0.00	0.00	0.00	0.02	0.00
Covenant Violations	0.00	0.01***	0.07	0.04	0.00
Qualified Auditors' Opinion	0.00	0.01	0.00	0.04	0.00
Year 2000 Issue?	0.01	0.01**	0.09	0.04	0.00
Family Company?	0.06	0.07***	0.44**	0.25	0.29
Override in Credit Model	0.04	0.01	0.04	0.04	0.05
Net Worth (logs)	8.37***	9.43***	11.01***	12.02*	11.75
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
Hard 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
Hard Risk Rating [1-7]	2.62	2.77***	3.33	3.32**	2.90
Hard Risk Rating [1-14]	5.94*	6.49***	8.04	7.89**	6.71
Soft 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
Soft 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	0.08			0.08	0.11	
	(0.01)			(0.01)	(0.02)	
Log Net Worth	0.15			0.15	0.19	
	(0.02)			(0.02)	(0.02)	
Classification Code	0.37		6.58	0.33	0.37	7.90
	(0.10)		(2.83)	(0.09)	(0.12)	(3.67)
Company Out Of Target Market	0.35		0.37	0.34	0.28	
	(0.14)		(0.13)	(0.13)	(0.16)	
Company Out Of Risk Acceptance	0.58		0.47	0.55	0.57	0.54
	(0.17)		(0.16)	(0.16)	(0.19)	(0.20)
Significant Increase in Facilities	0.94	1.02	1.01		1.05	1.15
	(0.38)	(0.38)	(0.35)		(0.43)	(0.44)
Adverse Change in Industry Outlook	0.55	0.51	0.47		0.58	0.58
	(0.22)	(0.24)	(0.21)		(0.25)	(0.25)
Family Company?	0.29		0.29		0.34	0.41
	(0.02)		(0.14)		(0.18)	(0.18)
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	0.46	0.48	0.54	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. Regressions include indicator variables for High level in columns (1), (2), (3) and (4) and indicator variables for all 5 levels in columns (5) and (6).

Dependent Variable	Log (Approved Credit)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Soft Rating	0.70	0.46	0.49	1.07	0.55	0.23	0.31
	(0.12)	(0.38)	(0.40)	(1.09)	(2.07)	(0.41)	(1.07)
Hard Rating	-0.05	0.09	0.29	0.28	0.73	0.12	0.20
	(0.03)	(0.09)	(0.27)	(0.24)	(1.38)	(0.10)	(0.24)
Soft Rating * High Level	-0.46	-0.73	-0.77	-0.66	-0.92		
	(0.22)	(0.27)	(0.26)	(0.29)	(0.48)		
Hard Rating * High Level	0.19	0.34	0.99	0.29	0.27		
	(0.05)	(0.07)	(0.19)	(0.07)	(0.11)		
Soft Rating * Level 2						-0.01	-0.03
						(0.25)	(0.27)
Soft Rating * Level 3						-1.00	-0.92
						(0.43)	(0.45)
Soft Rating * Level 4						-0.58	-0.62
						(0.34)	(0.37)
Soft Rating * Level 5						-0.98	-0.99
						(0.36)	(0.37)
Hard Rating * Level 2						0.04	0.08
						(0.06)	(0.06)
Hard Rating * Level 3						0.47	0.47
						(0.11)	(0.13)
Hard Rating * Level 4						0.23	0.27
						(0.08)	(0.09)
Hard Rating * Level 5						0.49	-0.45
						(0.10)	(0.10)
Powers of Rule Variables and their interactions with Hard and Soft Ratings.		1	1	1, 2	1	1	1, 2
Loan Officer Fixed Effects and their interactions with Hard and Soft	No	No	No	No	Yes	No	No
No. of Obs.	424	424	424	424	424	424	424
Adj R-sq / Pseudo R-sq	0.22	0.44	0.43	0.49	0.45	0.48	0.53

TABLE V
SENSITIVITY OF INFORMATION TO DIFFERENT OUTCOME MEASURES

Dependent Variable	Log (Outstanding)		Direction of Change		
	OLS		Probit		Ordered Logit
	(1)	(2)	(3)	(4)	(5)
Soft Rating	0.56	0.04	0.28	0.47	0.43
	(0.15)	(0.39)	(0.13)	(0.67)	(0.28)
Hard Rating	0.11	0.11	-0.11	-0.23	-0.13
	(0.03)	(0.09)	(0.10)	(0.42)	(0.12)
Soft Rating * High Level	-0.43	-0.67	-0.70	-0.75	-0.43
	(0.24)	(0.34)	(0.20)	(0.38)	(0.32)
Hard Rating * High Level	0.15	0.25	0.39	0.49	0.46
	(0.07)	(0.08)	(0.18)	(0.29)	(0.26)
Powers of Rule Variables and their interactions with Hard and Soft Ratings.		Yes		Yes	Yes
No. of Obs.	424	424	424	424	424
Adj R-sq / Pseudo R-sq	0.17	0.40	0.02	0.20	0.22

TABLE VI
GEOGRAPHIC DISTANCE

PANEL A: Selection Level 3

Variable	Mean In Branch [n=17]	Mean Out Branch [n=37]
Organizational Structure Variables		
Number of Approval Signatures	2.29***	2.76
Time To Prepare Credit Folder (days)	13.59	20.89
Time To Approve Credit (days)	12.29***	29.35
Revise and Resubmit Case	0.06**	0.38
Extra Client Information Requested	0.41	0.38
Hard Information		
Size Rating	2.94	2.44
Financial Risk Rating	11.12	11.94
Hard Risk Rating [1-7]	3.35	3.32
Hard Risk Rating [1-14]	8.00	8.05
Soft Information Variables		
Industry Position	3.53	3.43
Competitive Position	4.16*	3.68
Management Quality	4.13	3.72
Risk Management Policies	3.51	3.43
Access to Capital	4.38**	3.55
Soft Risk Rating	3.65	3.40
Other Variables		
Total Facilities (in Million $)	15.13	13.91
Total Outstanding (in Million $)	4.67	9.98
Net Sales (in Million $)	489.78**	219.95
Net Income (in Million $)	18.87	12.72
Net Worth (in Million $)	173.03	124.79
Leverage	1.69	1.94

TABLE VI
GEOGRAPHIC DISTANCE

PANEL B: Regression Analysis

Dependent Variable	Log of Approved Credit				
	All Levels			Only Level 3	
	(1)	(2)	(3)	(4)	(5)
Hard	0.14	0.45	0.60	0.32	0.32
	(0.05)	(0.13)	(0.15)	(0.13)	(0.15)
Soft	0.23	0.61	0.80	-0.35	-0.15
	(0.20)	(0.57)	(0.63)	(0.54)	(0.66)
In Headquarters	-1.05	-0.28	-0.36	0.93	1.24
	(0.82)	(0.89)	(1.40)	(1.64)	(1.95)
In Headquarters* Hard	-0.18	-0.35	-0.43	-0.34	-0.33
	(0.06)	(0.07)	(0.09)	(0.14)	(0.19)
In Headquarters* Soft	0.45	0.92	0.89	0.63	0.57
	(0.23)	(0.27)	(0.34)	(0.39)	(0.36)
Out Headquarters			0.55		
			(1.43)		
Out Headquarters*Hard			-0.28		
			(0.11)		
Out Headquarters*Soft			0.49		
			(0.38)		
Powers of Rule Variables and their interactions with Hard and Soft Ratings.		Yes	Yes		Yes
No. of Obs.	424	424	424	54	54
Adj R-sq / Pseudo R-sq	0.21	0.37	0.39	0.27	0.60

TABLE VII
DECOMPOSING SOFT INFORMATION

Dependent Variable	Log of Approved Credit								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soft Rating/Soft 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)		
Hard 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)
Soft Rating * High Level	-1.14	-1.13							
	(0.23)	(0.23)							
Hard Rating * High Level	0.33	0.33	0.22	0.27	0.27	0.21	0.26	0.18	0.33
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.09)	(0.06)
Industry * High Level			-0.42					-0.21	
			(0.32)					(0.30)	
Competitive Position * High Level				-0.51				-0.47	
				(0.16)				(0.25)	
Management* High Level					-0.61			-0.44	
					(0.16)			(0.25)	
Risk Management * High Level						-0.34		0.11	
						(0.26)		(0.27)	
Access Capital * High Level							-0.45	0.00	
							(0.12)	(0.19)	
Less Soft Score (Objective)									0.44
									(0.26)
More Soft Score (Subjective)									0.46
									(0.20)
Less Soft Score * High Level									-0.42
									(0.37)
More Soft Score * High Level									-0.67
									(0.30)
Definition of Soft Rating	Average	Weighted	Industry	Competition	Management	Risk Management Policies	Access Capital	All	Obj/Sub
Definition of Hard 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 Hard and Soft Ratings.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer Fixed Effects and their interactions with Hard and Soft	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
DECOMPOSING HARD INFORMATION

Dependent Variable	Log of Approved Credit			
	(1)	(2)	(3)	(4)
Soft Rating	0.45	0.44	0.33	
	(0.41)	(0.41)	(0.45)	
Financial Rating	0.00	0.00		-0.16
	(0.14)	(0.05)		(0.04)
Size Rating	0.15	0.16	0.32	0.33
	(0.26)	(0.26)	(0.11)	(0.11)
Financial Rating * High Level	0.42	0.13		0.31
	(0.11)	(0.04)		(0.10)
Size Rating * High Level	0.22	0.21	0.28	0.27
	(0.13)	(0.13)	(0.12)	(0.12)
Soft Rating * High Level	-0.90	-0.88	-0.81	-0.77
	(0.23)	(0.23)	(0.22)	(0.23)
Financial Score			-0.07	
			(0.02)	
Financial Score * High Level			0.13	
			(0.03)	
Definition of Hard Rating	Bank's	Bank's	Bank's	Average
Powers of Rule Variables and their interactions with Hard and Soft Ratings.	Yes	Yes	Yes	Yes
Loan Officer Fixed Effects and their interactions with Hard and Soft	Yes	Yes	Yes	Yes
No. of Obs.	405	405	405	322
Adj R-sq / Pseudo R-sq	0.55	0.55	0.54	0.53

TABLE IX
IMPACT OF HUMAN CAPITAL

Dependent Variable	Log of Approved Credit			
	(1)	(2)	(3)	(4)
Soft Rating	0.76	0.41	0.64	0.49
	(0.12)	(0.46)	(0.12)	(0.45)
Hard Rating	-0.08	0.10	-0.03	0.07
	(0.04)	(0.11)	(0.03)	(0.11)
Soft Rating * High Level	-0.74	-0.99	-0.41	-0.68
	(0.24)	(0.32)	(0.23)	(0.32)
Hard Rating * High Level	0.27	0.41	0.18	0.36
	(0.06)	(0.08)	(0.05)	(0.07)
Soft Rating * High Level * Tenure	0.69	0.86		
	(0.41)	(0.53)		
Hard Rating * High Level * Tenure	-0.25	-0.15		
	(0.09)	(0.12)		
Soft Rating * Tenure	-0.23	-0.26		
	(0.12)	(0.33)		
Hard Rating * Tenure	0.09	0.01		
	(0.06)	(0.07)		
Soft Rating * High Level * Compensation			-0.09	-0.09
			(0.46)	(0.67)
Hard Rating * High Level * Compensation			0.06	0.09
			(0.20)	(0.20)
Soft Rating * Compensation			0.28	0.25
			(0.21)	(0.49)
Hard Rating * Compensation			-0.09	-0.09
			(0.11)	(0.12)
Powers of Rule Variables and their interactions with Hard and Soft Ratings.		Yes		Yes
Loan Officer Fixed Effects and their interactions with Hard and Soft		Yes		Yes
No. of Obs.	424	424	424	424
Adj R-sq / Pseudo R-sq	0.24	0.48	0.23	0.48

APPENDIX A
HARD INFORMATION DECOMPOSITION VARIABLES

Hard Information Variable	Mean	SD	Min.	Max.	Obs.
Ratio Values					
Pre-tax Interest Coverage (dec.)	-2.05	91.12	-1316.00	284.11	405
Pre-tax Funds Flow Interest Coverage (dec.)	2.49	81.70	-1254.50	322.87	405
Funds from operations/Total Debt (%)	13.68	49.38	-27.74	700.00	405
Free Oper Cash Flow/Total Debt %	15.19	204.09	-21.59	4100.00	405
Pre-Tax Return on Avg Capital %	0.23	2.99	-30.29	23.25	404
Total Debt / Capitalization %	0.39	0.83	-14.27	4.71	405
Current Ratio (dec.)	1.37	1.32	0.00	13.42	405
Ratio Scores (0-22)					
Pre-tax Interest Coverage	11.00	7.99	0	22	405
Pre-tax Funds Flow Interest Coverage	11.38	7.68	0	22	405
Funds from operations/Total Debt (%)	10.25	7.85	0	22	405
Free Oper Cash Flow/Total Debt	10.22	8.69	0	22	405
Pre-Tax Return on Avg Capital %	9.42	8.67	0	22	403
Total Debt / Capitalization %	14.24	6.21	0	22	405
Current Ratio	7.04	5.88	0	22	405
Implied Ratings (1-7)					
Pre-tax Interest Coverage	4.46	2.54	1	8	405
Pre-tax Funds Flow Interest Coverage	4.57	2.47	1	8	405
Funds from operations/Total Debt (%)	4.19	2.52	1	8	405
Free Oper Cash Flow/Total Debt	4.27	2.73	1	8	405
Pre-Tax Return on Avg Capital %	3.97	2.76	1	8	403
Total Debt / Capitalization %	5.39	2.08	1	8	405
Current Ratio	3.16	1.85	1	8	405
Rating Score	10.49	5.58	0	21	404
Financial Rating	4.19	1.67	1	8	406
Size Test	2.30	1.44	1	6	406

APPENDIX B
SOFT INFORMATION DECOMPOSITION VARIABLES

Soft 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
Competitive Position					
Market Position	4.28	1.47	1	7	409
Product Line Diversity	3.88	1.12	1	7	409
Operating Cost Advantage	3.46	0.89	1	7	409
Technology Advantage	3.70	0.92	1	7	409
Key Success Factors	3.67	0.84	1	7	409
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
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	409
Access to Capital					
Capital Markets	3.47	1.11	1	7	409
Banks	3.77	1.01	1	7	409
Overall Business Ratings	3.47	0.66	1	5	409