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Estimating the Effect of Hierarchies on Information Use

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

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Do hierarchies effect the sharing of information within a firm? The evolution of firms from family businesses to large hierarchical organizations sparked an extensive debate on how the design of hierarchies impacts information sharing and allocation of tasks [Radner (1993); Bolton and Dewatripont (1994); Aghion and Tirole (1997); Garicano (2000); Stein (2002); Dewatripont and Tirole (2005); and Garicano and Rossi-Hansberg (2006)]. A central idea in this literature argues that information sharing —particularly when information is subjective and more nuanced in nature— becomes harder in more hierarchical production processes. However, despite the practical relevance of understanding how hierarchical design impacts information flows, empirical testing remains elusive.

There are several difficulties in empirically testing informational theories relating to hierarchical design. First, theoretical constructs such as "subjective information," "authority," and "hierarchical design" often lack a formal empirical counterpart and are thus difficult to measure. Second, theories of organizational design are often based on *intra-firm* dynamics, such as the sharing of information between employees within a firm. Such intra-firm transactions are seldom recorded in a form that can be analyzed. Third, even if the necessary data were available, there remains the challenge of finding plausibly exogenous variation in hierarchical design. For example, differences in how information is used across various hierarchical designs may be primarily driven by omitted factors that happen to be correlated with hierarchical design.

This paper addresses these empirical hurdles to estimate the effect of *hierarchical distance*, i.e. distance between a decision-making officer and his subordinate who collects information, on the *type* of information used in the decision-making process. A number of theories suggest that private non-verifiable information, which we classify as "subjective information," is difficult to use across organizational layers.[1] The precise channels vary from *ex-ante incentives* for information collection [Aghion and Tirole (1997); and Stein (2002)], to *strategic manipulation* of information [Crawford and Sobel (1982)] and *ex-post communication costs* [Sah and Stiglitz (1986); Radner (1993); and Bolton and Dewatripont (1994)]. However, regardless of the underlying channels, these papers share the common hypothesis that hierarchical distance makes it harder to use subjective information, hence increasing reliance on objective information.

We test the above prediction using data from the loan approval process of a large multi-national bank. The data is constructed using credit dossiers of large corporate loan applicants, and offers a natural environment for testing the impact of hierarchical distance on information use. First, the loan approval process is heavily dependent on information regarding an applicant's quality and future outlook. Second, the credit dossiers enable us to observe the flow of information (both objective and subjective) between the loan officer collecting information on an applicant, and the ultimate credit approval officer. Third, there is significant variation across applicants in the hierarchical distance travelled by a loan application. For example, some loan applications are approved by credit approval officers who sit very close (in terms of hierarchical distance) to the loan officers who collect information. While others are approved by credit approval officers who sit further away from information collecting officers in the hierarchy. An important feature of the hierarchical distance travelled by a loan application is that it is determined ex ante by "bank rules." This can be exploited to generate plausibly exogenous variation in hierarchical distance across applicants.

Our empirical methodology in this paper can be better understood from the following representative example. Consider a loan officer who receives a firm's loan application, and then collects a variety of information about the firm. For simplicity, summarize this information into a subjective signal (S) that represents the loan officer's personal assessment of the firm (for example, an "A" in "Management Professionalism"), and an objective signal (H) representing firm performance [for example, "10%" in Return on Assets (ROA)].

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

Next suppose that for some firms the loan officer cannot make the loan approval decision. Instead, after collecting signals S and H for these firms, he must send the loan application "upwards" to his boss (the manager) for approval. Will the manager give the same importance to the two signals as the loan officer? The theoretical literature cited earlier suggests this is not the case. For example, knowing that he no longer has discretion over the final decision, the loan officer might put less effort in collecting S, hence reducing its degree of informativeness [Aghion and Tirole (1997); and Stein (2002)]. Alternatively he might strategically add noise to S [Crawford and Sobel (1982)]. Thus when signals S and H reach the manager, S would have lost part of its informativeness. The same is not true of H (i.e., audited financials) since this signal is verifiable. Hence weights $\beta_S^{'}$ and $\beta_H^{'}$ used by the manager will be such that $\beta_S^{'} < \beta_S$ and $\beta_H^{'} > \beta_H$. In other words, credit approved by the manager will be less sensitive to subjective and more sensitive to objective information compared to credit approved by the loan officer (see Section 1 for full details).

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

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

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

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

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

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

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

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

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

There is a vast theoretical literature related to many of the issues our paper touches upon, but a review is not feasible here. Overall our results are in line with the view that greater hierarchical distance discourages the use of subjective and more abstract information. Although we discuss possible interpretations at the end, we want to emphasize that our primary purpose is not to discriminate between various theories that might lead to this reduced reliance on subjective information. In contrast, Liberti (2004) provides support for the loan officers' incentives view in Stein (2002) by showing that loan officers who receive relatively more formal authority as opposed to real authority put more effort into collecting soft information from their large corporate borrowers.

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

1 Information and Hierarchies

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

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

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

(3) Ex-Post Communication Costs - Work such as, Becker and Murphy (1992), Radner (1993), and Bolton and Dewatripont (1994) focuses on the ex-post costs of communication, and argues that while hierarchies provide advantages such as specialization and parallel processing, they also bring trade-offs in the form of costly communication across hierarchical levels. Such costs are likely to be larger for subjective information that is harder to verify by a third party.

While the work cited above differs in its foundations, it shares a common theme. The literature predicts that introducing layers between employees generating information and those taking decisions, leads to difficulties in generating and transmitting information, particularly subjective information that is softer in nature. It is this particular prediction that we take to data, and remain mostly agnostic as to which of the three classes of theories might generate the observed empirical relationships.

1.1 Empirical specification

We motivate our empirical specification through an example that closely mirrors how our data is generated. 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 1. A loan officer sits at the lower level and his manager at the higher level. The loan officer is responsible for receiving and reviewing each loan application. The review process involves collecting a variety of information about the firm. We summarize this information into two types: an objective signal H and a subjective signal S. The objective signal consists of easily quantifiable information such as size, profitability (e.g., 10% ROA), and other audited financial ratios. The subjective signal on the other hand is qualitative in nature and includes information such as the loan officer's assessment (e.g., a grade of "A") of firm's management quality and project strength.

Insert Figure 1 Approximately Here

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, the final authority to decide what amount, L, should be given to a firm can rest with either the loan officer or his manager. Both loan officer and manager decide on L depending on firm quality Q, with higher quality firms getting larger loan amounts. However, loan officer and manager differ in terms of how they determine Q given informational signals H and S. In-line with the theoretical work, suppose that S loses part of its informativeness when it is used by someone higher up in the hierarchy (manager in our example) who did not collect this information. H on the other hand is based on objective information that everyone can interpret and verify and hence does not lose informativeness (to the same extent at least) when used across hierarchical layers.

For example, H may include a firm's ROA during the last three years as recorded in audited firm financials. S on the other hand may include the subjective score given by the loan officer regarding the quality of the firm's new management. If the loan officer has to communicate these two signals to the manager, an ROA of say 10% can be communicated without much loss of information. However, a subjective management quality grade of say "A" is much harder to interpret for a bank manager, and the quality of this information depends on loan officer's incentives.

Formally if one defines "informativess" of a signal as its covariance with the underlying metric of interest Q, then theory predicts that the covariance drops faster for subjective information when communicated across hierarchical levels. This gives us the following empirical prediction[2]:

$$L_{ij} = \alpha + \beta_1 \times MGR_{ij} + \beta_H \times H_{ij} + \beta_H^M \times (H_{ij} \times MGR_{ij}) + \beta_S \times S_{ij} + \beta_S^M \times (S_{ij} \times MGR_{ij}) + \varepsilon_{ij} \tag{1}$$

L_{ij} is the log of approved credit for firm i whose information is collected by loan officer j. MGR_i is an indicator variable equal to 1 if firm i is approved by the manager, and 0 if firm i is approved by the loan officer. The main prediction is that $\beta_H^M > 0$ and $\beta_S^M < 0$, i.e., sensitivity of the credit approval decision to subjective information is smaller for managers than loan officers, and vice versa for objective information. There is no particular prediction on the level of sensitivity to subjective and objective information [i.e., coefficients β_H and β_S in (1)].

We have deliberately used the term "subjective" rather than "soft" to denote the more nuanced information. A strict definition of soft information makes it impossible to be codified and hence (by assumption) soft information cannot be observed by an econometrician. Subjective information, on the other hand, can be categorized into grades. However, such grades do not have a well-specified objective metric like height, weight, or profitability, and hence cannot be objectively "verified" by a third party.

2 Data Description

We estimate Equation (1) using data from a bank whose organizational structure closely mirrors the description in Section 1. The data covers information contained in the credit folders of *all* of the 424 corporate clients of a large multi-national bank in Argentina in 1998. A firm is classified as corporate by the bank if its annual net sales exceed 50 million pesos.[3] The advantage of having full access to these credit folders is that we observe the entire life cycle of loan origination. 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, the geographical location of the final approving officer, and the approved and requested loan amounts.

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

The pre-specified set of rules in the credit manual guarantee that the loan officer has no discretion in determining the final level of credit approval for a firm. This is rational for a profit maximizing bank. If the bank believes that the loan officer does not have sufficient capability to approve a loan for certain firms, then it would not want the loan officer to decide what those firms are.[4] There are five different levels of approval in the hierarchical design of our bank, with the loan officer sitting at the lowest level (see Figure 2).

Insert Figure 2 Approximately Here

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 divide variables constructed from the credit folders into *approval level 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.

2.1 Approval level rule variables

Given the five hierarchical levels in the bank, Table 1 shows how firms are distributed across these levels for credit approval. The loan officer himself approves at Level 1 26.7% of loans.[5] Another 37.3% are approved at Level 2, and the remaining are approximately equally divided among Levels 3, 4, and 5.

Firms are sent to one of the five hierarchical levels as determined by the rule variables. Although theoretically there are 19 rule variables, many of these are "exceptions" that are used very rarely. In particular there are 11 such variables that *taken together* influence the approval level of only 48 firms in sample.[6] For brevity we do not report their summary statistics, although they will be included in the regression analysis later on.

The eight primary variables responsible for assigning applicants to different approval levels are described in Appendix A, and their averages by the five approval levels are given in Panel A of Table 1. These variables include applicant characteristics such as: loan maturity and level of collateralization, applicant loan size, central bank credit score, foreign bank branch guarantee, family company indicator, and indicator variables for whether a firm belongs to a pre-specified industry or fails to pass an industry "threshold level."

It should be kept in mind that credit manual guidelines that map rule variables to approval levels cannot be expressed in a single closed form function. There are a number of discontinuities and trigger points built into the credit manual guidelines. For example, larger applicants are more likely to be sent to higher levels for approval. However this relationship is not smooth, and by necessity there are cut-off points deciding the level of firms. Similarly a number of other reasons, such as maturity structure, firm industry, and credit score can send a firm to higher levels for approval even if the firm falls in a lower level according to applicant size. It is thus a combination of several non-linear rules that decides the ultimate approval level for a firm.

General principles underlying assignment rules can be understood from Panel A of Table 1 that provides means of all rule variables broken down by the five approval levels. The means shows that firms requesting larger loans are more likely to be sent to higher levels for approval. Since bigger firms have larger and more complex funding requirements, the bank is more inclined to send such firms to officers higher up in the hierarchy as they have more experience and expertise. Similarly, firms belonging to volatile industries, poor credit history, long-term loans and unsecured loan applications are more likely to be sent to higher levels for approval. On the other hand, firms with guarantees from foreign affiliates of the bank are unlikely to be sent up for approval. These patterns again reflect the belief that more senior officers are better able to evaluate more complex loans.

Insert Table 1 Approximately Here

Table 2 formally investigates the relationship between the approval level and rule variables used by the bank's credit manual to allocate firms across levels. Column (1) includes *all* of the (19) rule variables on the right-hand side, and reaffirms that larger applicants, applicants with worse credit scores, firms with more complex loan requests, and firms belonging to volatile or nascent industries are more likely to be sent to higher levels for approval. These results are very much in line with the "management by exception" criteria of Garicano (2000), where the role of a hierarchy is to conserve the time of experts so that they only intervene when no one else can solve a problem. Although Column (1) includes all of the rule variables used by the bank, the R^2 is still only 0.42. These low R^2 reflect 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^2 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 in all of the 424 firms in our sample.

Insert Table 2 Approximately Here

Column (2) of Table 2 includes all pair-wise interactions of the top four rule variables to allow for some non-linearities. The top four rule variables are Maturity/Collateral Score, Applicant Size, Central Bank Credit Score, and Foreign Bank Branch Guarantee. The R^2 increases to 0.54. Column (3) adds higher powers of the rule variables by including functions of powers 2 and 3 for all the 19 rule variables. The R^2 increases slightly to 0.55 as a result. Column (4) shows that most of the variation in approval levels is explained by the top four rule variables as these four variables alone give us an R^2 of 0.34 compared to 0.42 in Column (1).

Since approval levels only take integer values, OLS may not be an appropriate estimation technique. Correspondingly we experiment with ordered probit and ordered logit specification in Columns (5) and (6). However, even with such non-normal estimation techniques Pseudo R^2 is not very high.

2.2 Informational variables

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

Our data set includes all of the objective and subjective pieces of information collected by the loan officer as per bank rules. The bank pre-specifies what pieces of information have to be collected by a loan officer. In order to avoid concerns of "data mining," we desist from picking and choosing any particular set of informational variables. Instead, we use *all* of the informational variables collected by a loan officer. These variables are naturally classified by the bank into two categories: objective cardinal and subjective ordinal measures.

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

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

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

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

Although we stick with the bank's construction of objective and subjective indices (to avoid concerns of data mining), our results are completely robust to alternative definitions of objective and subjective indices as we shall discuss in the robustness section. Panel B of Table 1 provides the mean and standard deviation of information indices by the level of approval. The variation in information indices is similar across the five levels of approval. This is useful since we estimate the sensitivity of loan approval to information separately at different approval levels. Since some of our regression specifications use loan-officer fixed effects, we also report standard deviation in subjective and objective indices after demeaning these variables at the loan officer (i.e., information collecting agent) level. As Panel B shows, there is significant variation across the five levels even within the same loan officer.

Table 3 provides the correlation matrix for the various sub-components of subjective and objective indices. The sub-components are positively correlated as expected. However, the correlation is not perfect, signifying the independent component that each sub-component brings to the overall indices. We shall explore the variation in sub-components in some of the analysis as well.

Insert Table 3 Approximately Here

2.3 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, otherwise 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 and there is significant variation in this amount across firms as shown in Panel A of Table 1. The approved credit line aggregates all the 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. The difference between approved and outstanding amounts partly reflects liquidity management on part of the 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 three years, percentage 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.

3 Empirical Methodology

3.1 Identification

We can estimate Equation (1) using data on subjective and objective information indices (S and H) for loan applicants approved at different hierarchical levels of approval. However, the concern is that differences in sensitivity of credit to information may be driven by the endogenous assignment of loan applicants to various approval levels, rather than a direct effect of hierarchical distance. We outline these concerns in more detail below.

3.1.1 Endogenous bank assignment

As we have outlined, the bank follows a systematic set of rule to assign applicants to various approval levels. A concern therefore is that firms sent to higher levels for approval are inherently different in terms of how important objective and subjective information is in evaluating them. For example, perhaps firms with less reliable subjective information are deliberately sent further up in the hierarchy because more senior bank officers are better able to tackle complicated loans with poor subjective information. If this were the case, managers will put less weight on subjective information compared to loan officers even if there was no effect of hierarchical distance on information use.

More generally, 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 3 shows the function mapping Z to approval level. The endogeneity concern is that larger firms might have less relevant subjective information, and/or more relevant objective information. This can be represented statistically by plotting how the "informativeness" of subjective and objective information varies with Z.

Insert Figure 3 Approximately Here

Let σ^2_{qs} and σ^2_{qh} denote the covariance of subjective and objective information respectively with firm quality Q. Furthermore, suppose $\overline{\sigma^2_{qh}}$ and $\overline{\sigma^2_{qs}}$ denote the maximum possible informativeness for a firm, i.e., the informativeness that the best loan officer can generate if he works efficiently. Then the general concern is that any bank assignment criteria Z might be positively correlated with $\overline{\sigma^2_{qh}}$ and/or negatively correlated with $\overline{\sigma^2_{qs}}$. Figure 3 plots some possible relationships between Z and $\overline{\sigma^2_{qs}}$, and Z and $\overline{\sigma^2_{qh}}$ that can bias β^M_S downwards and β^M_H upwards respectively.

The endogenous bank assignment concern highlighted in Figure 3 is almost impossible to address if Z is unknown or not observable. However, as pointed out, the bank has a pre-specified list of rule variables (i.e., Z's) that determine which level a firm gets sent to. Moreover, these rule variables are based on third-party verifiable objective criteria and not subject to the loan officer's discretion. We can therefore control for endogenous bank assignment concerns by including Z, and its interactions with subjective and objective information ($Z \times S$) and ($Z \times H$) as controls in (1). We can also include higher powers of Z (such as Z^2) and their interactions with H and S to allow for greater functional form flexibility.

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

3.1.2 Endogenous loan officer assignment

A separate concern in estimating (1) is the endogenous assignment of loan officers to firms. Since information for all types of firms is collected by the loan officers, it might be the case that firms approved by loan officers themselves are given to loan officers with better ability and expertise in collecting subjective information. If this were the case, then firms approved by loan officers will get higher weight on subjective information not because of the lower level of approval, but because the loan officer was better at collecting subjective information.

Since we know the identity of the loan officer, j, collecting information for each firm, i, we can fully address the loan officer selection concern by including loan officer fixed effects, and interacting these fixed effects with H and S. This non-parametric approach ensures that we only compare firms at different approval levels whose information was collected by the *same* loan officer. Bank selection controls and loan officer fixed effects (α_j) update (1) to:

$$L_{ij} = \beta_H^M(H_{ij} \times MGR_{ij}) + \beta_S^M(S_{ij} \times MGR_{ij}) + \alpha_j + \alpha_j H_{ij} + \alpha_j S_{ij} + \beta_1 MGR_{ij} + \beta_2 Z_i + \beta_3(H_{ij}Z_i) + \beta_4(S_{ij}Z_i) + \varepsilon_{ij} \tag{2}$$

4 Results

4.1 Effect of hierarchy on information use

We estimate Equation (1) using the data and methodology described above. We begin by collapsing the five approval levels into "high" and "low" around the median. This classifies approval Levels 1 and 2 as "low," and Levels 3, 4, and 5 as "high." Column (1) of Table 4 estimates Equation (1) using the log of approved credit line as the dependent variable. Coefficients on interaction between the information indices and the high level dummy show that the 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 a high level. These results are consistent with theoretical predictions.

Insert Table 4 Approximately Here

However, as Section 3 explained, the result may also be driven by endogenous assignment of firms and/or loan officers. Column (2) of Table 4 includes loan officer fixed effects and their interactions with objective and subjective indices. There are a total of 26 loan officers. The fixed effects non-parametrically control for the person generating subjective and objective information, and force comparison between firms whose objective and subjective information is generated by the *same* loan officer.[7] The results are very similar to those of Column (1).

Column (3) of Table 4 controls for endogenous bank assignment concern by including variables used by the bank to assign firms to different levels as controls. We include the 19 rule variables described in Appendix A, as well as their interactions with objective and subjective information indices as controls on the right-hand side. In other words, Column (3) tests the full blown specification in equation (2) that exploits the non-linearities in bank assignment rules to identify our coefficients of interest. Our coefficients of interest remain qualitatively unchanged. It is worth emphasizing that the amount of loan requested by an applicant is one of the controls in Column (3). In other words, both right- and left-hand side variables are conditioned on the amount of loan requested by an applicant. Since we are exploiting non-linearities in rule approval to identify our coefficient of interest in Column (3), the increase in objective information sensitivity and decrease in subjective information sensitivity at higher levels is unlikely to be driven by spurious bank assignment criteria.

The magnitude of the effect of hierarchical distance is large. As all informational variables have already been normalized, the coefficients can be interpreted as the effect of a one standard deviation change in information variables. Then for a firm with a 1% higher objective information score (in s.d. units), getting approved at the higher (more distant) hierarchical level increases its approved credit limit by about 0.8%. Of course if the same firm also had 1% higher subjective information score, then it would lose out by about 0.7% if approved at the higher level. Thus the net effect really depends on the correlation of objective and subjective scores across firms. The information in Table 3, Panel C is instructive here. It shows that subjective and objective information indices are positively correlated, and the correlation magnitude is strong.

The coefficient on objective information is essentially zero at low level of approval (Column (1) of Table 4). However, if we take out subjective information from Column (1), then objective information is positive at the low levels as well. In other words, it is the component of objective information that is orthogonal to subjective information that is not given any weight in the credit making decision by officers at low levels. It is a bit puzzling that objective information caries no significant (independent) weight in the evaluation of loans at low level. One possible explanation is that when loan officers know that they themselves (or close associates) are approving the loan, they incorporate all necessary information (in their view) into the subjective information grades. Thus once this subjective information is taken into account, there is no residual power in the objective information index.

We also explore the robustness of our results to concerns that they might be driven spuriously by firm attributes such as firm size, firm profitability, and industry fixed effects in Column (4). However, inclusion of these variables as controls does not effect our coefficients of interest qualitatively.

Columns (5) and (6) of Table 4 open up these five levels to see how the sensitivity to information changes at each level. Column (5) includes loan officer fixed effects and their interactions with information indices, while Column (6) adds bank selection criteria variables and their interactions with information indices as well. The results show that the change in credit sensitivity is not gradual across the five 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.

4.2 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 the organizational structure of the loan approval process, then how are approvals at Level 2 so much different from approval at Level 3, but not from approval at Level 1?

The geographical location of officers at different hierarchical levels presents a possible explanation. Our data includes information on the location of each loan officer involved in the loan process. Panel A of Table 5 shows the joint distribution of the level of approval, and the geographical distance between a loan officer and the officer approving a given loan. The variable, geographical distance, is defined as 0 if the loan officer who collects information and the loan approving officer are located in the same branch. Otherwise it is coded as 1. The joint distribution shows that loan officers collecting information and loan approval officers at Level 2 *always* are located in the same bank branch. They can therefore interact and communicate on a daily basis with ease and are likely to know each other quite well. Since there is equal sensitivity to objective and subjective information among Level 1 and Level 2 approvals, it suggests that communicating subjective information among co-workers who work in close geographical proximity is easy.

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

Insert Table 5 Approximately Here

We exploit variation in location of the loan approving officer to formally test whether the results in Table 5 were driven by the loss in informativeness due to officers sitting at different geographical locations. Column (1) of Table 5 of Panel B re-runs Column (1) of Table 4, but replaces hierarchical distance with geographical distance. The results show that the change in sensitivity to information happens when the approving officer and the loan officer collecting information are at different locations . However, as Panel A showed, geographical and hierarchical distance are highly correlated. The only independent variation in geographical distance occurs for loans approved at Level 3. Therefore, Column (2) restricts the 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 is located in the same branch as the loan officer, his sensitivity to subjective information is much higher than a Level 3 officer located outside the loan officer's branch. Similarly, sensitivity to objective information increases when the officer sits outside the branch of the loan officer.[8] Column (3) repeats Column (2) on the full data, but includes all the approval level dummies and their interactions with informational indices. It thus replicates Column (2), but is more efficient for computing standard errors. The results are almost identical.[9]

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.

4.3 Are more experienced loan officers better at communicating subjective information?

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

Since we have information on the experience of a loan officer within the bank, we can test whether this experience facilitates subjective information communication. We do so through our loan officer fixed effects specification and add triple interactions of subjective and objective information sensitivities with loan officers' experience. The median loan officer has six years of experience in the bank. There is a break in the loan officer tenure distribution at seven, and as such we use seven years' experience as the cutoff point to create a dummy for "experience." The results in Columns (1) and (2) of Table 6 show that the decline in subjective information sensitivity is much smaller for more experienced loan officers.[10]

Insert Table 6 Approximately Here

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.

4.4 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 the 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 weigh 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. (1) AVGsubjective: This is a simple arithmetic mean of all the 18 subjective information variables, and (2) 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 7 repeat the primary regression specification but replace subjective information rating with AVGsubjective and WAVGsubjective respectively. The result on credit sensitivity to subjective information is 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.

Insert Table 7 Approximately Here

Subjective information variables also differ in their "subjectiveness" or the extent of subjectivity involved in computing them. If sensitivity to subjective information declines as a result of communication losses across hierarchies, then one would expect such losses to be greater for more subjective variables. We therefore divide subjective variables according to the degree of subjectivity involved in computing them and split the subjective index into a strong subjective index, and a weak subjective index (Section 2 explained their construction).

Columns (3) through (5) of Table 7 test whether the drop in sensitivity to subjective information at higher levels is stronger for more subjective information. The results indicate that the drop in sensitivity of subjective information is stronger for the more subjective sub-index. This result is also in-line with our earlier results and interpretation that it is the subjectivity of information that makes it difficult to communicate across hierarchies. For example, consider the components of the weak subjective index. In coming up with industry outlook indices, a loan officer may use publicly verifiable industry data such as recent growth and volatility. Rating a firm's leverage or liquidity policy can also be judged to a reasonable extent from its balance sheet numbers. Similarly access to capital data is generally available in verifiable formats such as central credit registry data or knowing the number of relationships the firm has access to.

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

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

5 Discussion of Results

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

Section 1 explained that a number of different theories all suggest that hierarchical distance should favor objective over subjective information. Given that our results confirm this common prediction, we now outline which economic interpretation is more favorable in the light of our results.

5.1 Loss in communication

One interpretation of our results is based on theories of costly communication. In particular, subjective information may be more costly to communicate across hierarchies, particularly when communicating parties are geographically separated, and when the person generating information has been with the bank for a brief period of time. Subjective information is harder to communicate between people who do not work together since they are not fully aware of each other's 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 when the loan officer has spent the least time in the bank.

5.2 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 and use 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) and tested in Liberti (2004). An incentive based explanation is more likely to effect subjective information acquisition since this type of information requires more effort and thinking on the part of the loan officer. For an incentive based story to explain all of our results, we will have to assume that the loss of incentives is not great when the person making the final credit decision works in close geographical proximity to 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 the 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.

5.3 Strategic manipulation of information

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

However, we feel that strategic manipulation is unlikely to be a main explanation of our results. Loan officers must also have an incentive to provide accurate and useful information to their superiors in order to maximize their chances of promotion and career development. Such incentives should suppress the desires to manipulate information. Similarly, the effect of strategic manipulation should have been seen when the 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 is located in a separate branch. This evidence also lowers the likelihood of strategic manipulation as a primary explanation of our results.

5.4 Different abilities or objectives

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

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

5.5 Corruption or related lending

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

6 Concluding Remarks

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

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

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

Appendix A: Description of Approval Level Rule Variables

There are eight primary approval level rule variables described below:

- Maturity/Collateral Score: This is the bank's numerical indicator on a scale of 1 to 10 (including subgrades) to identify the overall risk associated with each specific facility/loan of the firm. The bank's scale follows the following scheme: 1 (best), −2, 2, +2, −3, 3, +3, −4, 4, +4, −5, 5, +5, −6, 6, +6, −7, 7, +7, 8, 9, and 10 (worse). We scaled this score using a numerical indicator between 1 (worst) and 22 (best). The bank's pre-specified rules map the worse of the scores for each of the loans granted to the firm into a corresponding approval level. The score is based on both the maturity of the facilities and the level of collateralization. The score is lower if credit facilities are short term (relative to long-term) and secured or guaranteed (relative to unsecured and subordinated). Maturity refers to the length of time from the current date to the maturity or expiration of the loan contract.
- Applicant Loan Size: This is the total amount of credit facility (in millions) requested by the firm.
- Central Bank Credit Score: This is the credit score reported by the Argentinean Central Bank Public Credit Registry (Central de Deudores del Sistema Financiero CDSF) for an applicant. The score is based on the applicant's past credit history from all the banks in Argentina. The numerical rating is expressed on a scale of 1 to 5, where: 1= Current/Accrual Basis, 2 = Evidence of Weakness, 3 = Substandard/Timely Repayment is at Risk, 4 = Doubtful/Timely Repayment is Improbable, and 5 = Uncollectable/Write-off.
- Foreign Bank Branch Guarantee: This is a dummy variables that captures when the parent company of a foreign subsidiary firm or "support provider" provides commercial and financial support to its local subsidiary. The risks that the bank is asked to assume are only nationalization, expropriation, and convertibility. Foreign guarantees from the affiliates cover the financial and commercial risk.
- Family Company?: This dummy variable captures whether the company is private or in the case of a public corporation, whether it is controlled by family members.
- Product Market Industry Benchmark: This variable is 1 if a firm's product scope and scale is below a pre-specified industry benchmark.
- Financial Risk Industry Benchmark: This variable is 1 is a firm's past financial performance is below a pre-specificed industry benchmark.
- Declining Industry: This variable is 1 if a firm belongs to the set of industries pre-specified by the bank as "declining." Industries are classified into 27 categories and they are expressed at the 2-digit SIC (Standard Industrial Classifications) Code.

In addition to the above eight variables, there are 11 additional rule variables (called "exceptions") that are used very rarely. In particular, these 11 variables *taken together* influence the approval level of only 48 firms in sample. They are all binary 0-1 variables and include: Requested Amount Above Pre-Approved Limits According to Firm Size, Downgrade in Firm's Credit Score, Increase In Total Facilities Requested, Reported Risk Event At The Firm, Adverse Change In Risk Profile of The Firm, Adverse Change In Industry, Change in Type of Collateral and/or Degree of Support, Covenant Violations, Qualified Auditors, Loan Documentation Completion, and Internal Bank Debt Rating Model Not Used.

Appendix B:

Objective information variables

This table reports summary statistics of the objective information variables used in the paper. All sub-components are reported both in raw form and as an implied rating. The bank translates the ratios according to a pre-specified formula into a rating that goes from 0 to 22 for the sub-components of the *Performance Index*, and from 1 to 6 for the component of the *Size Index*. For 30 firms the sub-components of the *Performance Index* measure are missing, hence the total number of firms is 394. All measures are in book values. *Pre-Tax Interest Coverage* is the ratio of (Net Income from Operations – Gross Interest Expense – Income Tax – Net Sale of Equity)/Gross Interest Expense. *Pre-Tax Funds Flow Interest Coverage* is the ratio of (Free Cash Flow – Gross Interest Expense – Income Tax – Net Sale of Equity)/Gross Interest Expense. *Funds from Operations/Total Debt* is the ratio of Net Income from Operations/Total Debt where Total Debt is composed by Short- and Long-Term Debt. *Free Operating Cash Flows/Total Debt* is the ratio of Free Cash Flow/Total Debt. *Pre-Tax Return on Average Capital* is the ratio of (Net Income from Operations – Gross Interest Expense – Income Tax)/(Total Debt + Net Worth + Minority Interest). *Total Debt/Capitalization* is the ratio of Total Debt/(Total Debt + Net Worth + Minority Interest). *Current Ratio* is the ratio of Total Current Assets over Total Current Liabilities. *Firm Size* is the total capitalization of the firm.

Objective Information Variable	Mean	SD	Min.	Max.	Obs.
Sub-Component of Objective Index (Raw Form)					
Performance Index					
Pre-tax Interest Coverage (dec.)	4.68	8.12	-8.47	23.62	394
Pre-tax Funds Flow Interest Coverage (dec.)	7.79	10.71	-7.02	30.90	394
Funds from operations/Total Debt (%)	12.18	35.55	-0.73	121.37	394
Free Oper Cash Flow/Total Debt (%)	5.12	14.92	-1.24	50.38	394
Pre-Tax Return on Avg Capital (%)	0.06	0.24	-0.59	0.54	394
Total Debt / Capitalization (%)	0.42	0.28	0.00	0.92	394
Current Ratio (dec.)	1.25	0.65	0.32	2.86	394
Size Index					
Firm Size	411,250	4,102,483	-102,675	84,000,000	424
Sub-Component of Objective Index (Implied Rating)					
Performance Index					
Pre-tax Interest Coverage	10.98	8.01	0.00	22.00	394
Pre-tax Funds Flow Interest Coverage	11.39	7.71	0.00	22.00	394
Funds from operations/Total Debt	10.21	7.86	0.00	22.00	394
Free Oper Cash Flow/Total Debt	10.34	8.66	0.00	22.00	394
Pre-Tax Return on Avg Capital	9.40	8.68	0.00	22.00	394
Total Debt / Capitalization	14.17	6.23	0.00	22.00	394
Current Ratio	7.14	5.86	0.00	22.00	394
Size Index					
Firm Size	2.26	1.43	1.00	6.00	424
Standardized Objective Indices					
Objective Index	0.00	1.00	-1.90	3.22	424
Performance Index	0.00	1.00	-1.88	2.47	424
Size Index	0.00	1.00	-0.89	2.62	424

Appendix C:

Subjective information variables

This table reports summary statistics of the subjective information variables, the primary components and the sub-components used in the paper reported in Appendix D. There are a total of 18 primary subjective information variables, divided across five subjective information categories. The main categories of the *Subjective Index* are *Industry Risk Assessment*, *Competitive Position*, *Management Quality*, *Risk Management Policies*, and *Access to Capital*. All ratings are reported by the loan officer and are between 1 (worse) and 7 (best). The Mean Category is the average across the fields for each of the categories. There are 15 firms that have the sub-component level information missing, therefore reducing the sample to 409 firms. Furthermore, for three firms, some *Competitive Position* variables are not relevant, therefore reducing the sample to 406 firms.

Subjective Information Variable	Mean	SD	Min.	Max.	Obs.
Industry Risk Assessment					
Trend in Output	3.51	0.80	1.00	7.00	409
Trend in Earnings	3.27	0.78	1.00	7.00	409
Cyclicality	3.35	0.81	1.00	7.00	409
External Risks	3.53	0.71	2.00	5.00	409
Mean Category	3.41	0.59	1.75	5.00	409
Competitive Position					
Market Position	4.28	1.47	1.00	7.00	407
Product Line Diversity	3.88	1.12	1.00	7.00	408
Operating Cost Advantage	3.46	0.89	1.00	7.00	406
Technology Advantage	3.70	0.92	1.00	7.00	406
Key Success Factors	3.67	0.84	1.00	7.00	406
Mean Category	3.80	0.81	1.00	6.60	408
Management Quality					
Professionalism	3.67	0.90	1.00	7.00	409
Systems and Controls	3.66	0.89	1.00	7.00	409
Financial Disclosure	3.72	0.85	1.00	7.00	409
Ability to Act Decisively	3.77	0.80	1.00	7.00	409
Mean Category	3.70	0.75	1.00	6.50	409
Risk Management Policies					
Leverage Policy	3.34	0.85	1.00	7.00	409
Liquidity Policy	3.36	0.86	1.00	7.00	409
Hedging Policy	3.60	0.86	1.00	7.00	409
Mean Category	3.43	0.72	1.00	6.30	409
Access to Capital					
Capital Markets	3.47	1.11	1.00	7.00	409
Banks	3.77	1.01	1.00	7.00	409
Mean Category	3.62	0.98	1.00	7.00	409
Standardized Subjective Indices					
Overall Subjective Index	0.00	1.00	-3.75	2.32	424
Strong Subjective Index	0.00	1.00	-3.85	3.58	409
Weak Subjective Index	0.00	1.00	-3.35	3.56	409

Appendix D:

Assessment criteria of subjective information variables

This table reports the assessment criteria of the subjective information variables. These are a series of qualitative questions answered by the loan officer when completing the loan request dossier. The qualitative questions and responses are as follows:

BUSINESS RISK ASSESSMENT

1 Competitive Position	RR1-2	RR3	RR4	RR5	RR6	RR7
Market Position	Below 2% / Minor Player; Declining Share	2 to 3% / Minos Player	Over 5% / Known Player or Established Niche	Over 10% / Major Player or Strong Niche	Over 20% / Dominant	Over 50% / Clearly Dominant
Product Line Diversity	Only 1 Declining Line	Only 1 Stable Line	At least 2 Stable Lines	At least 2 Growing Lines	Over 3 Lines	Over 3 Growing Lines
Operating Cost Advantage	High Cost Producer	No Cost Advantages	Some Cost Advantages	Has Lowest Local Costs	Achieves Low Global Costs	Global Leader
Technology Advantage	Predominantly Outdated	Technology Follower	Mostly New; Upgrading Old	Leader in Local Market	Global Player in Some Areas	Global Leader in Many Areas
Key Success Factors	None	Strong in Some; Weak in Others	Strong Locally in Some Factors	Strong Locally in All Factors	Global Capabilities in Most Factors	Global Capabilities in All Factors

2 Management	RR1-2	RR3	RR4	RR5	RR6	RR7
Professionalism	In Few Positions	At Some Key Positions	At Most Key Positions & Most Levels	At all Key Posi- tions in Operations & Management	At all Levels in Operations & Management	At all Levels With Extensive Experience
Systems and Controls	Largely Absent	Unreliable	Acceptable	Very Reliable and Strong	Meets Highest Local Standards	Meets Highest Global Standards
Financial Disclosure	Unreliable	Delayed, Inaccu-rate or Incomplete	Satisfactory Reporting	Usually Timely and Accurate	Always Timely and Accurate	Meets Highest Global Standards
Ability to Act Decisively	Hopeless	Weak	Good, but Untested	Good, but Untested	Proven to be Strong	Proven to be Very Strong

3 Risk Management Policies	RR1-2	RR3	RR4	RR5	RR6	RR7
Leverage Policy	Unlimited Appetite	High Tolerance	Some Tolerance	Low Tolerance	Very Conservative	Extremely Conservative
Liquidity Policy	No Policy	Low Liquidity Acceptable	Maintains Some Cushion	Some Cushion & Sound Contingency Plan	Conservative Cushion & Contingency Plan	Extremely Conser- vative Cushion
Hedging Policy	No Hedging Policy / Speculative Policy	Risks Understood but Most Not Covered	Risks Understood but Not Always Covered	Most Risks Understood; Few Open Positions	Most Risks Understood; No Open Positions	All Risks Understood; No Open Positions

4 Access to Capital	RR1-2	RR3	RR4	RR5	RR6	RR7
Capital Markets	No access to Capital markets	Limited Largely to Domestic Banking	Primarily Domes-tic Banking; Some Capital Markets	Primarily Domestic; Some International	Wide Access; Domestic & International	Wide Access; Domestic & International
Banks	Bank Cutting Lines; Some Locked-in	No Bank Strongly Committed or Some Banks Getting Out	At Least One Bank Strongly Committed	At Least One Bank Strongly Committed	Established Re- lationships; Strong Commitments	Established Re- lationships; Strong Commitments

5 *Industry*	RR1-2	RR3	RR4	RR5	RR6	RR7
Trend in Output	Declining	Uncertain / Declining	Stable	Growth	Strong Growth	Very Strong Growth
Trend in Earnings	Declining	Uncertain / Declining	Stable	Growth	Strong Growth	Very Strong Growth
Cyclicality (Fluctuations)	Large & Unpredictable	Large	Moderate	Small	Very Limited	Very Stable
External Risks	Widespread Risks	Numerous Critical Risks	Variuos Critical Risks	Few Critical Risks	Few Risks, Non Cyclical	No Risks

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Notes

[1]Hayek (1945 p.524) 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."

[2]A formal proof was provided in an earlier version of the paper, which is available from the authors upon request.

[3]In 1998 the bank was ranked third in terms of total assets and fifth 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. As per Law 23,928 "Ley de Convertibilidad del Austral" from March 27, 1991, $1 Argentine Peso was equivalent to 1 US Dollar.

[4]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.

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

[6]These variables are all binary 0-1 variables. They are: Requested Amount Above Pre-Approved Limits According to Firm Size, Downgrade in Firm's Credit Score, Increase In Total Facilities Requested, Reported Risk Event At The Firm, Adverse Change In Risk Profile of The Firm, Adverse Change In Industry, Change in Type of Collateral and/or Degree of Support, Covenant Violations, Qualified Auditors, Loan Documentation Completion, and Internal Bank Debt Rating Model Not Used.

[7]We do not report coefficients on loan officer fixed effects, and their interactions with Subjective index and Objective index for brevity sake. Also note that due to the inclusion of these interactions, the coefficient on the subjective and objective indexes only reflects the omitted loan officer category and is hence not shown.

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

[9]Since we are only using the the 54 firms from Level 3 for identifying our coefficient of interest, we no longer have sufficient power to include the loan officer fixed effects, rule variables, and their interactions with information indices.

[10]Defining the "experience" dummy at the break in the distribution is important for our results. For example, the triple interaction results lose significance if we define the "experience" above median.

Figure 1: An example of bank hierarchical structure

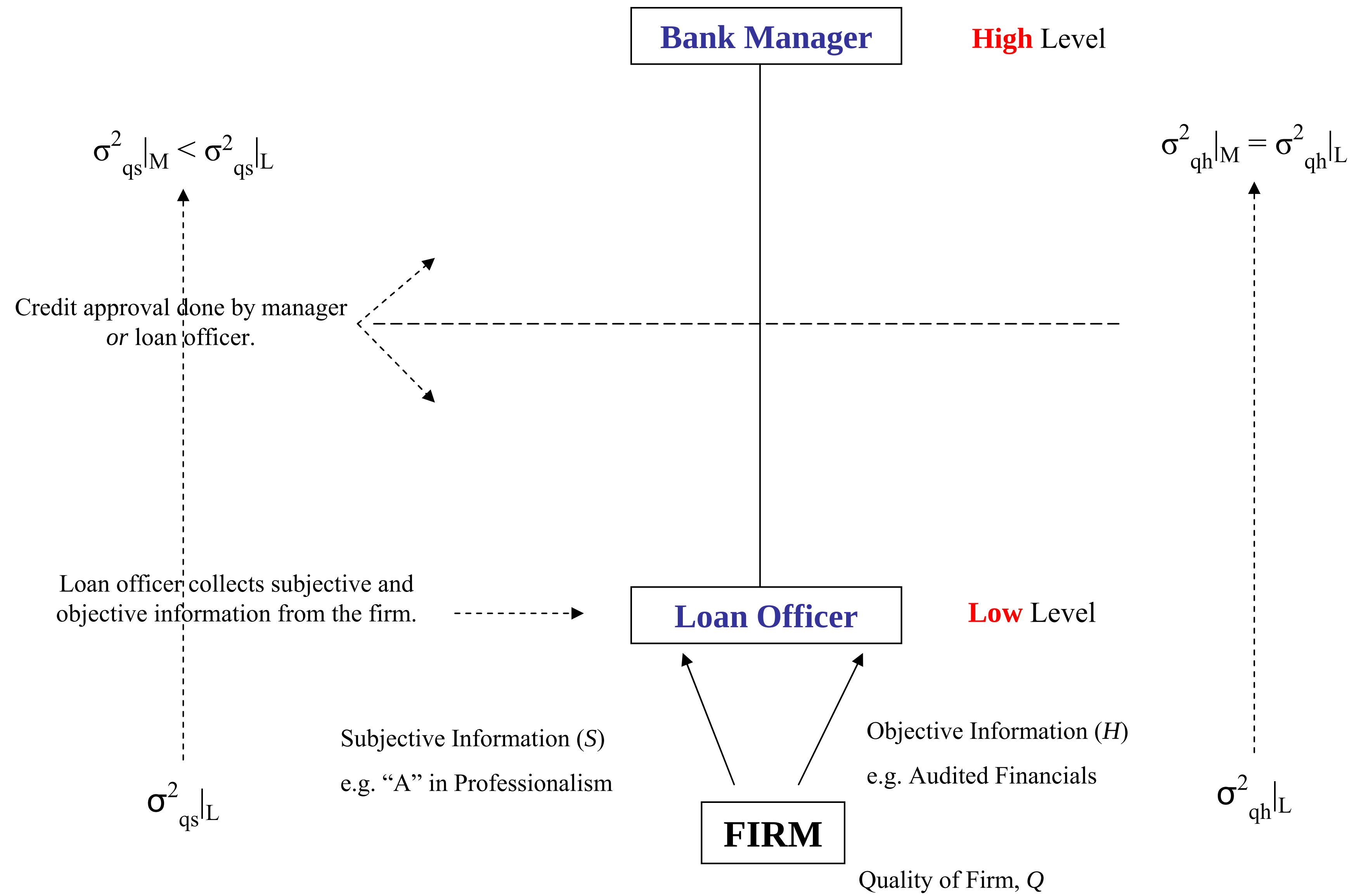

Figure 2: Hierarchical decision-making process

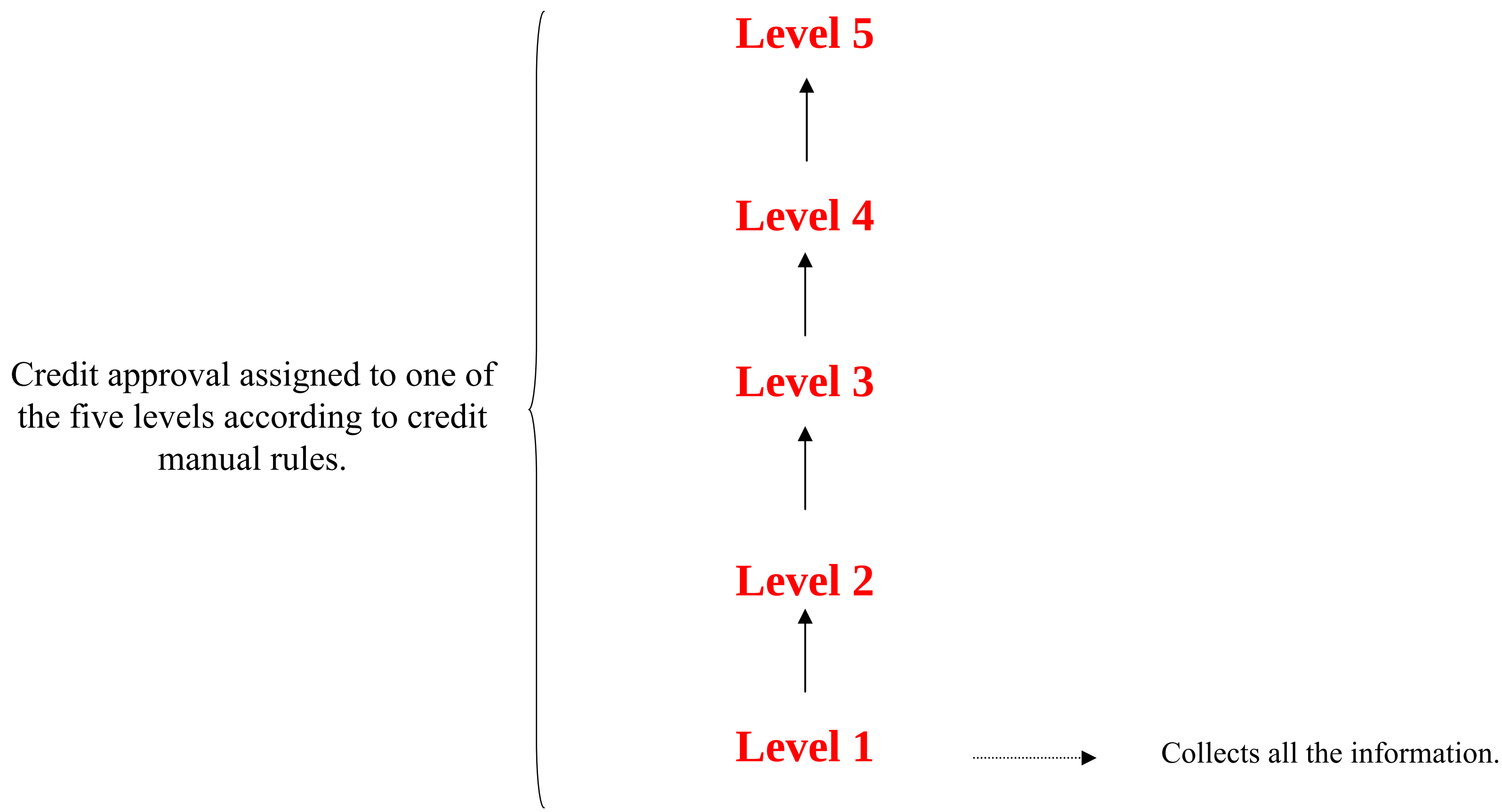

Figure 3: Empirical strategy

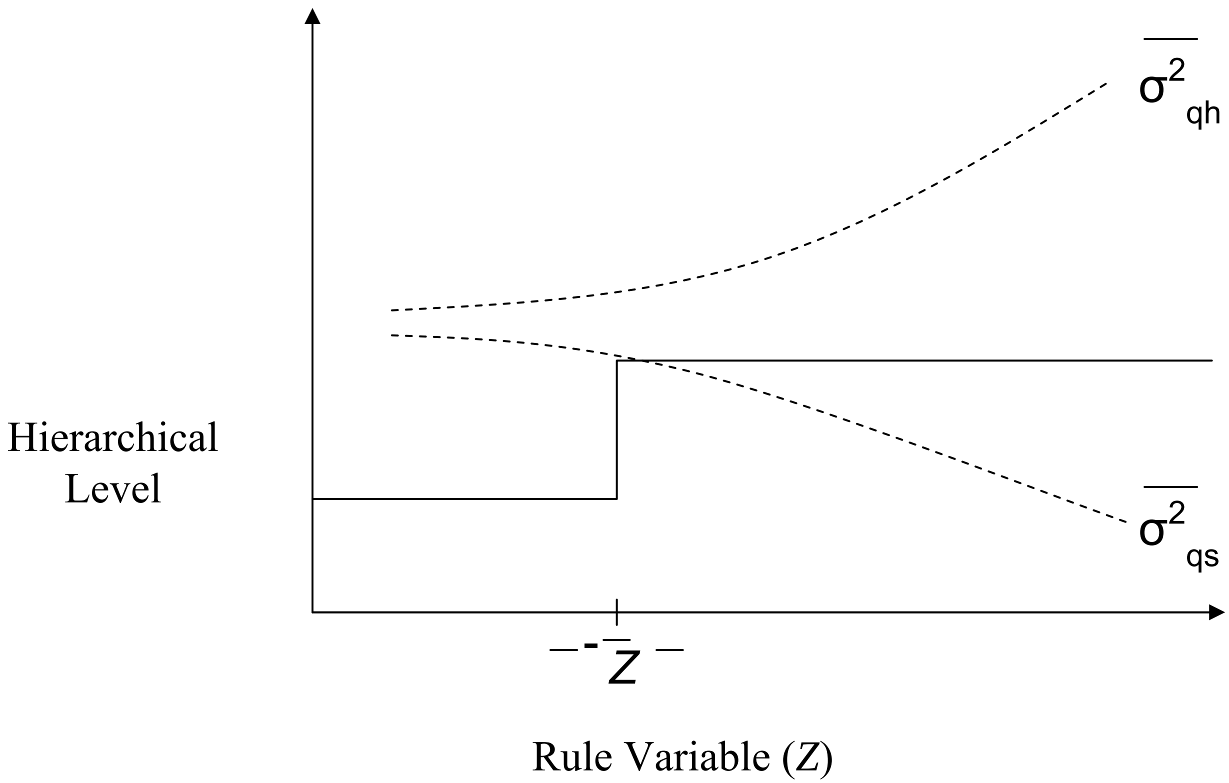

TABLE 1
Summary statistics

The table presents summary statistics for the main variables used in the paper by a loan's approval level. Approval Level Rule Variables determine how firms are allocated across approval levels (Levels 1 through 5) by the bank. Panel A shows the eight primary approval level rule variables. There are an additional 11 rule variables that are used occasionally. The complete list (and definitions) of rule variables is given in Appendix A. Panel B provides summary stats on Information Indices that are constructed using information collected by a loan-officer on an applicant firm. The *Objective Index* is constructed using a firm's audited financial ratios and size (see Appendix B for details), while the *Subjective Index* is constructed using a subjective assessment of various firm attributes (see Appendix C for details).

	Level 1	Level 2	Level 3	Level 4	Level 5
Number of Firms	113	158	54	57	42
Percentage of Firms	26.7%	37.3%	12.7%	13.4%	9.9%
PANEL A: Means of Variables By Approval Level					
Approval Level Rule Variables					
Maturity / Collateral Score	9.61	11.89	14.37	14.42	16.40
Applicant Size (in Million $)	6.06	17.15	17.20	39.05	36.98
Central Bank Credit Score	1.06	1.09	1.24	1.23	1.88
Foreign Bank Branch Guarantee	0.77	0.02	0.01	0.00	0.00
Family Company?	0.06	0.07	0.44	0.25	0.29
Product Market Industry Benchmark	0.13	0.10	0.50	0.61	0.50
Financial Risk Industry Benchmark	0.02	0.05	0.35	0.40	0.33
Declining Industry	0.04	0.02	0.24	0.09	0.00
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
Total Assets (in Million $)	64.83	145.87	293.21	862.43	1,333.80
PANEL B: Mean and Standard Deviation of Information Variables By Approval Level					
Mean					
Objective Index	-0.37	-0.19	0.36	0.66	0.34
Performance Index	0.01	-0.08	0.35	-0.03	-0.23
Size Index	-0.56	-0.21	0.17	1.00	0.72
Subjective Index	-0.32	-0.09	0.02	0.57	0.41
Strong Subjective Index	-0.32	-0.14	0.13	0.36	0.48
Weak Subjective Index	-0.25	-0.15	0.14	0.40	0.44
Standard Deviation					
Objective Index	0.85	1.04	0.78	0.76	1.12
Subjective Index	0.83	0.97	0.87	1.07	1.16
Objective Index (Demeaned at Loan Officer Level)	0.86	1.01	0.71	0.65	1.08
Subjective Index (Demeaned at Loan Officer Level)	0.85	0.94	0.82	0.84	0.97

TABLE 2
Mapping of rule variables to level of approval assignment

This table predicts approval level based on functions of rule variables used in the credit manuals to assign loan applicant firms to approval levels. The dependent variable is the *Approval Level*, which varies from 1 to 5. All regressions include the 19 rule variables described in Appendix A, but coefficients on only the eight primary rule variables are shown for brevity. Columns (1) to (4) report Ordinary Least Squares (OLS) estimates while Columns (5) and (6) report Ordered Probit estimates. Column (1) only includes the 19 rule variables as controls. Column (2) adds 16 pair-wise interactions of the four top rule variables: *Maturity/Collateral Score*, *Applicant Size*, *Central Bank Credit Score*, and *Foreign Bank Branch Guarantee*. Column (3) further includes powers 2 and 3 of the 19 rule variables, i.e., a total of 38 additional controls. Column (4) only includes the four top rule variables on the right hand side. In Columns (3) and (6), *Foreign Bank Branch Guarantee/Family Company?,* and *Family Company?,* respectively, are dropped due to perfect collinearity.Robust standard errors clustered at the holding company level are reported in parenthesis.

Dependent Variable	Approval Level					
	OLS				Ordered Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
Maturity / Collateral Score	0.09	0.06	-0.39	0.12	0.12	0.51
	(0.01)	(0.06)	(0.20)	(0.01)	(0.02)	(0.14)
Applicant Size	0.01	0.03	0.04	0.01	0.01	0.05
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Central Bank Credit Score	0.31	1.36	6.71	0.29	0.29	1.29
	(0.10)	(0.51)	(2.93)	(0.10)	(0.12)	(0.70)
Foreign Bank Branch Guarantee	-0.02	-0.29		-0.32	0.42	
	(0.12)	(0.45)		(0.11)	(0.14)	
Family Company?	0.32	0.25			0.44	
	(0.16)	(0.15)			(0.18)	
Product Market Industry Benchmark	0.48	0.30	0.29		0.55	0.36
	(0.15)	(0.13)	(0.13)		(0.16)	(0.17)
Financial Risk Industry Benchmark	0.60	0.41	0.35		0.62	0.45
	(0.17)	(0.15)	(0.15)		(0.18)	(0.19)
Declining Industry	-0.52	-0.67	-0.68		-0.51	-0.81
	(0.23)	(0.20)	(0.20)		(0.25)	(0.25)
Pair-wise Interaction Of Top 4 Rule Variables		Yes	Yes			Yes
Powers 2 and 3 of Rule Variables included?			Yes			Yes
No. of Obs.	424	424	424	424	424	424
Adj R-Sq / Pseudo R-Sq	0.42	0.54	0.55	0.34	0.19	0.29

TABLE 3
Correlation of matrix of information indices and their sub-components

This table reports the correlation between information indices and their sub-components. See Appendix B and Appendix C for variable description and summary statistics for these variables.

PANEL A: Correlation Matrix for Sub-Components of Objective Index

	Pre-tax Interest Coverage	Pre-tax Funds Flow Interest Coverage	Funds From Operations / Total Debt	Free Oper. Cash Flow/Total Debt	Pre-Tax Return on Avg Capital	Total Debt / Capitalization	Current Ratio	Firm Size
Pre-tax Interest Coverage	1.00							
Pre-Tax Funds Flow Interest Coverage	0.91	1.00						
Funds From Oper/Total Debt (%)	0.67	0.75	1.00					
Free Oper. Cash Flow/Total Debt (%)	0.42	0.44	0.61	1.00				
Pre-Tax Return on Avg Capital (%)	0.66	0.53	0.62	0.38	1.00			
Total Debt / Capitalization (%)	0.40	0.44	0.68	0.47	0.27	1.00		
Current Ratio (dec.)	0.20	0.19	0.24	0.14	0.09	0.33	1.00	
Firm Size	0.13	0.12	0.04	0.03	0.03	0.03	-0.17	1.00

PANEL B: Correlation Matrix for Sub Components of Subjective Index

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

PANEL C: Correlation Matrix for Information Indices

	Objective Index	Performance Index	Size Rating	Subjective Index	Strong Subjective Index	Weak Subjective Index
Objective Index	1.00					
Performance Index	0.73	1.00				
Size Rating	0.73	0.06	1.00			
Subjective Index	0.46	0.23	0.44	1.00		
Strong Subjective Index	0.42	0.20	0.42	0.78	1.00	
Weak Subjective Index	0.43	0.22	0.40	0.79	0.77	1.00

TABLE 4
Does reliance of information vary with hierarchical distance?

This table estimates the credit sensitivity to objective and subjective information variables for firms getting credit approvals at various hierarchical levels within the bank. The dependent variable is the logarithm of the amount of credit approved, *Log(Approved Credit)*. *High Level* is an indicator variable that collapses the 5 approval levels into "high" and "low" around the median. *High Level* takes a value of 1 for Levels 3, 4, and 5; and a value of 0 otherwise. Columns (2) through (6) add loan office fixed effects and their interactions with the Subjective and Objective Information variables (75 additional controls in all). Columns (3), (4), and (6) further add the 19 rule variables used by the bank to assign firms to different levels and their interactions with Objective and Subjective Information measures (57 controls in all). The 19 rule variables are described in Appendix A. Columns (5) and (6) open up the five hierarchical levels to see how sensitivity to information changes at each level. The omitted category in these columns is *Level 1*. Robust standard errors clustered at the holding company level are reported in parenthesis.

Dependent Variable	Log (Approved Credit)					
	(1)	(2)	(3)	(4)	(5)	(6)
High Level	0.53	0.32	0.15	0.17		
	(0.15)	(0.19)	(0.26)	(0.27)		
Subjective Index	0.41	--	--	--	--	--
	(0.08)					
Objective Index	-0.04	--	--	--	--	--
	(0.06)					
Subjective Index × High Level	**-0.43**	**-0.78**	**-0.68**	**-0.60**		
	(0.13)	**(0.23)**	**(0.31)**	**(0.31)**		
Objective Index × High Level	**0.84**	**0.92**	**0.82**	**0.93**		
	(0.13)	**(0.29)**	**(0.28)**	**(0.31)**		
Subjective Index × Level 2					**-0.12**	**0.24**
					(0.17)	**(0.33)**
Subjective Index × Level 3					**-0.87**	**-0.76**
					(0.31)	**(0.40)**
Subjective Index × Level 4					**-0.91**	**-0.62**
					(0.36)	**(0.42)**
Subjective Index × Level 5					**-0.88**	**-0.74**
					(0.48)	**(0.53)**
Objective Index × Level 2					**0.25**	**-0.25**
					(0.14)	**(0.38)**
Objective Index × Level 3					**1.13**	**0.92**
					(0.40)	**(0.42)**
Objective Index × Level 4					**1.37**	**0.70**
					(0.39)	**(0.46)**
Objective Index × Level 5					**1.14**	**0.57**
					(0.38)	**(0.37)**
Constant	1.72	--	--		--	--
	(0.07)					
Rule Variables and Their Information Interactions			Yes	Yes		Yes
Loan Officer FE and Their Information Interactions		Yes	Yes	Yes	Yes	Yes
Industry FE, Firm Size, and ROA.				Yes		
Indicator Variables for each level					Yes	Yes
No. of Obs.	424	424	424	423	424	424
Adj R-sq	0.27	0.39	0.65	0.73	0.43	0.66

TABLE 5
Geographical distance

Panel A reports the joint distribution of the level of approval, and geographical distance between a loan officer and the ultimate officer approving a loan. Geographic Distance takes a value of 0 if the loan officer who collects information and the ultimate approving officer are located in the same branch; otherwise it is coded as 1. Panel B estimates the credit sensitivity to Objective and Subjective Information variables for firms getting credit approvals from officers located at different facilities. The dependent variable is the logarithm of the amount of approved credit, *Log(Approved Credit)*.

Panel A: Joint Distribution of Hierarchical and Geographical Distance

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

Panel B: Information Use and Geographical Distance

Dependent Variable	Log (Approved Credit)		
		Level 3 Only	
	(1)	(2)	(3)
Geographical Distance × Objective Index	**0.86** **(0.13)**	**0.89** **(0.45)**	**0.89** **(0.42)**
Geographical Distance × Subjective Index	**-0.44** **(0.14)**	**-0.36** **(0.38)**	**-0.36** **(0.36)**
Other Variables included in regression but coefficients not shown	*	*	**
No. of Obs.	424	54	424
Adj R-sq	0.27	0.28	0.34

* *Geographical Distance*, *Objective Index*, *Subjective Index*, and a *Constant*.
** *Geographical Distance*, *Objective Index*, *Subjective Index*, *Approval Level* indicator variables, and the interaction of these indicator variables with the *Objective Index* and the *Subjective Index*.

TABLE 6
Does experience help the use of subjective information?

This table tests whether the experience of a loan officer who collects information helps in the use of subjective information in the credit approval decision. *Tenure* is a dummy variable that takes a value of 1 when the years of experience in the bank are seven or more years and 0 otherwise. The dependent variable is the logarithm of the amount of approved credit, *Log(Approved Credit)*. Column (1) adds loan office fixed effects and their interactions with Subjective and Objective Information variables (75 additional controls in all). Column (2) further adds the 19 rule variables used by the bank to assign firms to different levels and their interactions with Objective and Subjective Information measures (57 controls in all). The 19 rule variables are described in Appendix A. Robust standard errors clustered at the holding company level are reported in parenthesis.

Dependent Variable	Log (Approved Credit)	
	(1)	(2)
Subjective Index × High Level × Tenure	**2.16**	**2.83**
	(0.56)	**(0.47)**
Objective Index × High Level × Tenure	**-1.16**	**-1.70**
	(0.65)	**(0.49)**
Rule Variables and Their Information Interactions		Yes
Loan Officer FE and Their Information Interactions	Yes	Yes
Other Variables included in regression but coefficients not shown	*	*
No. of Obs.	424	424
R-sq	0.40	0.66

* *Subjective Index*, *Objective Index*, *High Level*, *Subjective Index* × *High Level*, *Objective Index* × *High Level*, *Tenure*, *Tenure* × *Subjective Index*, *Tenure* × *Objective Index*, and *Tenure* × *High Level.*

TABLE 7
Decomposing subjective information

This table checks the robustness of the main results by using different measures of the *Subjective Index*. We construct two different measures of overall subjective information rank. *AVGsubjective* is a simple arithmetic mean of all the 18 subjective information variables. *WAVGsubjective* weighs the five categories that form the *Subjective Index* equally while giving equal weights to the subjective information variables within each category. *Strong Subjective Index* is a standardized average of the categories *Management Quality* and *Competitive Position*. *Weak Subjective Index* is a standardized average of the categories *Industry Risk Assessment*, *Risk Management Policies*, and *Access to Capital*. Columns (1), (2), (4), and (5) include loan office fixed effects and their interactions with Subjective and Objective Information variables (75 additional controls in all). The dependent variable is the logarithm of the amount of approved credit, *Log(Approved Credit)*. Columns (1), (2), and (5) further add the 19 rule variables used by the bank to assign firms to different levels and their interactions with Objective and Subjective Information measures (57 controls in all). The 19 rule variables are described in Appendix A. Robust standard errors clustered at the holding company level are reported in parenthesis.

Dependent Variable	Log (Approved Credit)				
	(1)	(2)	(3)	(4)	(5)
Subjective Index × High Level	**-0.68**	**-0.65**			
	(0.19)	**(0.19)**			
Objective Index × High Level	**0.85**	**0.84**	**0.90**	**0.87**	**0.85**
	(0.25)	**(0.25)**	**(0.13)**	**(0.27)**	**(0.25)**
Weak Subjective Index × High Level			**-0.18**	**-0.29**	**-0.23**
			(0.18)	**(0.21)**	**(0.20)**
Strong Subjective Index × High Level			**-0.40**	**-0.58**	**-0.52**
			(0.19)	**(0.20)**	**(0.19)**
Definition of Subjective Rating	Average	Weighted			
Rule Variables With Information Interactions	Yes	Yes			Yes
Loan Officer FE and Information Interactions	Yes	Yes		Yes	Yes
Other Variables included in regression but coefficients not shown	*	*	**	**	**
No. of obs.	409	409	409	409	409
Adj R-sq	0.73	0.73	0.29	0.42	0.74

* *Subjective Index*, *Objective Index*, and *High Level*.
** *Objective Index*, *Weak Subjective Index*, *Strong Subjective Index*, *High Level*, and a *Constant*.