Hardening Soft Information: Does Organizational Distance Matter?

Stefano Filomeni, Gregory F. Udell, and Alberto Zazzaro*

Abstract

A large literature has developed on the distinction between hard and soft information with much of this literature focused on displacement of soft information with hard information. We investigate whether the propensity of loan officers at local branches to incorporate soft information in the credit scoring process is affected by the geographical distance between the branch and the bank's headquarters. We find that hardening soft information is significantly sensitive to branch-to-headquarters distance. We also find that organizational distance affects time for loan approval, increasing approval time for applicants receiving a good credit score (i.e., low probability of default) originated at distant branches and reducing approval time for applicants with poor credit scores (i.e., high probability of default). Finally, we find that on average organizational distance has no direct impact on the likelihood of the occurrence of negative credit events. However, the final rating being equal, the hardening of soft information has an influence on loan performance that varies with organizational distance. Overall, our findings are consistent with the presence of spatially-based communication frictions within banking organizations.

Keywords: *Credit scoring, soft information, hard information, communication problems, bank organization*

JEL codes: G21, L14, D82

---

* Stefano Filomeni (corresponding author), stefano.filomeni@essex.ac.uk, University of Essex, Essex Business School, Finance Group (Colchester, UK); Gregory F. Udell, gudell@indiana.edu, Kelley School of Business, Indiana University, and MoFiR; and Alberto Zazzaro, alberto.zazzaro@unina.it, University of Naples Federico II, MoFiR, and CSEF.
We are grateful to two anonymous referees for their valuable insights and suggestions. We also thank Barbara Casu, Giovanni Ferri, Tommaso Oliviero, Giovanni Walter Puopolo, Janis Skrastins, Elena Tabacco and participants at seminars held at the CERBE (Rome, Italy), Euricse (Trento, Italy), Japan Finance Corporation Research Institute (Tokyo, Japan), JCR - European Commission (Ispra, Italy), Polytechnic University of Marche (Ancona, Italy), University College Dublin (Dublin, Ireland), University of Genoa (Genoa, Italy), University of Strathclyde (Glasgow, UK), and at Wolpertinger Conference 2016 (Verona, Italy) and 2017 MFA Annual Meeting (Chicago, USA) for providing very helpful comments on preliminary versions of this paper.

1. Introduction

A large literature has developed on the distinction between hard and soft information. Part of this literature explores the extent to which technology has enabled hard information to *displace* soft information. That is, much of the emphasis has been on the substitution of hard information for soft information and the trend toward using hard information in underwriting loans *instead* of soft information. Empirical findings that indicate that banks can now lend at a longer bank-to-borrower distance are consistent with this view of technological innovation in business lending (Petersen and Rajan, 2002). But, there is another channel that might explain the ascendency of hard information over soft information in the underwriting and monitoring of business loans: the "*hardening*" of soft information – that is, the transformation of soft information *into* hard information. In their recent overview paper on soft and hard information, Liberti and Petersen (2019) note that "one can always create a numerical score with soft information" but this *"in and of itself doesn't make the information hard"*. The authors also note that a "potential line of future research is to study the trade-offs of using complex numerical algorithms summarizing all of the information in a single credit score" … and the possibility that *"relevant information may be lost in translation, especially soft information"*. The purpose of our paper is to address this issue by assessing the ability - and limits - of banks in hardening soft information in a modern credit scoring framework.[1]

Stein (2002) provides a theoretical framework for thinking about the difficulty associated with the process of hardening soft information. In his model, the hierarchical structure of large banks and their associated incentive mechanisms will impede the transmission (i.e., the translation into hard information) of soft information and diminish its value in loan underwriting and monitoring. In the same vein, the geographical and cultural distances between the bank's peripheral branches and its decision-making centers *"makes difficult the exchange of qualitative and soft information"* (Fiordelisi et al., 2014), thus discouraging local loan officers from the hardening of soft information, and making senior managers at the bank headquarters mistrustful about hardened soft information coming from the periphery. To assess the ability of hierarchical banks to harden soft information we exploit

[1] The hardening of soft information in a credit scoring framework can be viewed as the standardization of the language in a banking organization in order to move the boundaries of soft information transmission across bank hierarchical layers (Crémer et al., 2007; Bloom et al., 2014). Indirect support for the role of credit scoring technology in mitigating communication frictions can be found in the rapid adoption of credit scoring by large banks with geographically dispersed branches and a decentralized organizational structure (Akhavein et al., 2005; Mocetti et al., 2017; Albareto et al., 2011), and the rapid increase of the amount of small business lending in markets far from the banks' headquarters (see Frame et al. (2004)). More directly, DeYoung et al. (2008), and Paravisini and Schoar (2013) show that the introduction of credit scoring techniques improves information processing and reduces asymmetries of information within a bank organization by making internal communication more reliable.

Stein's theoretical framework by examining the extent to which the geographical distance of loan officers in charge of loan applications from the bank decision-making centers diminishes their willingness and ability to harden soft information without loss of content in a commercial loan setting.

Our analysis recognizes that there are two distinct channels through which loan officers responsible for the credit score can quantify (i.e., harden) soft information and use it to modify the automated financial score. First, they may translate qualitative assessments of predetermined, specific borrower characteristics into a numerical score precisely as suggested by Liberti and Mian (2009). This type of hardening has been documented by regulators (BCBS, 2000; OeNB, 2004; Fed, 2011) and analyzed in a few academic papers (e.g., Brown et al., 2015). We refer to the use of this first type of hardening as *"codified discretion"*. The second type of hardening allows a loan officer to upgrade or downgrade a final rating. We refer to this as *"uncodified discretion"* – a type of hardening also documented by supervisors (BCBS, 2005; Fed, 2011) and in the academic literature (Brown et al., 2012; Brown et al., 2015; Gropp and Guettler, 2018). It is not uncommon to find both codified and uncodified discretion in the same rating scheme as was the case in the six banks studied in Brown et al. (2015).

Unlike the extant literature on hardening soft information, we offer a comprehensive analysis of the ability of banks to successfully transmit soft information within the bank's hierarchy, separately through these two distinct channels: codified and uncodified discretion. We investigate whether a bank's ability to incorporate hardened soft information in the credit scoring process diminish with the organizational distance between the loan officer and senior managers at the bank's headquarters. More specifically, we ask the following questions: Does the loan officers' propensity to exercise codified and uncodified discretion systematically vary with the branch-to-headquarters distance? Does the confidence that the bank attaches to credit scores generated at the local branches depend on organizational distance?

Our data on commercial loan underwriting at a large European bank is ideally suited to this analysis. In addition to loan level data on the quantitative input to the loan rating process, we also have information about the qualitative input in terms of both codified and uncodified discretion. Equally important, we have information on the time that has elapsed between the end of the scoring process and the final loan approval. Finally, we have granular information on each loan regarding the geographical location of the bank branch in charge of the loan application and its distance from the bank's headquarters and loan the branch. We believe that this information on distance affords the strongest test of Stein's theoretical prediction. To the best of our knowledge, ours is the first paper that combines all of these elements in a loan-level analysis: information on the hardening of soft information, the time taken for lending decisions, and the branch-to-headquarters (i.e., organizational) distance for each loan application.

Our main results indicate that there are some significant limits to the hardening of soft information. That is, we find that the adoption of hardening technology in credit scoring does not completely eliminate communication problems across bank hierarchical layers and the adverse effects of spatially-based organizational frictions in lending (Fiordelisi et al., 2014; Levine et al., 2019). First, we find that organizational distance influences loan officers' hardening of soft information in credit scoring. On the one hand, we find that loan officers located in branches at a greater distance from the main bank headquarters are more likely to inflate the credit score by submitting positive numerical responses to the codified questions about borrower characteristics. On the other hand, we find the opposite with respect to uncodified discretion. That is, we find that loan officers located in branches at a greater distance from the main bank headquarters have a significantly lower probability of using uncodified discretion. Second, we find that on average loan approval decisions on applications scrutinized by loan officers at distant branches take statistically significantly more (less) time when the credit score generated by the loan officer indicates a low (high) probability of default. Finally, we find that on average organizational distance has no direct impact on the likelihood of the occurrence of negative credit events. However, the final rating being equal, the hardening of soft information has an influence on loan performance that varies with organizational distance. Overall, our findings provide evidence of the limited ability of banks to harden soft information in a way that survives communication within the bank's hierarchy.

The rest of this paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the dataset and the credit scoring process employed by our bank. Section 4 introduces the empirical strategy and describes all the dependent and explanatory variables used in the econometric analysis. Section 5 discusses main empirical results on discretion and the injection of soft information in credit scoring along with some additional and robustness tests. Section 6 concludes.

2. Related Literature

Our findings contribute to a fast growing literature on loan officer discretion, information production and manipulation in credit-scored lending (Puri et al., 2011; Bouwens and Kroos, 2012;

Brown et al., 2012; Campbell, 2012; Berg et al., 2013; Berg, 2014; Degryse et al., 2014; Mosk, 2014; Nakamura and Roszbach, 2018; Campbell et al., 2019). Perhaps in a paper most closely related to our research, Gropp and Guettler (2018) measure the discretionary use of soft information as the difference between the final and the hard-information-based ratings (this difference we label as *"discretion_1"*) and show that loan officers at small savings banks in Germany are more likely to upgrade the financial rating of applicants than their colleagues at large savings banks, while the downgrades of financial ratings are not significantly different between the two groups of banks. Our paper differs from Gropp and Guettler (2018) in two major ways. First, we identify the location of our loan officers and assess the impact of communication frictions in information transmission related to the exact within-bank geographical distance between bank officers and bank decision-makers rather than just proxying for communication frictions with the size of the bank. Second, the credit score building process is segmented into components that allow us to distinguish between two channels through which loan officers can inject their subjective information, each characterized by a different type of subjective knowledge, codifiable and uncodifiable, and by a different exposure of loan officers to possible reputation and career effects.

In another related paper Brown et al. (2015) consider the use of discretion by loan officers in the credit scoring process at six Swiss banks. Like us, they also distinguish between a codified discretion – specifically, the qualitative assessment of the applicant based on loan officer answers to seven predefined questions required by the banks – and an uncodified discretion – the override of the applicant's rating based on a detailed report about the reasons for the proposed override. They document that, when discretion in the scoring process has to be approved by a credit manager, loan officers tend to increase the qualitative assessment of applicants more than the likelihood of overriding. Brown et al. (2015), however, do not analyze how hierarchical distance within a large bank matters. Thus, we extend this line of investigation by focusing on the communication frictions associated with geographical distance in a Stein (2002) hierarchical setting – the distance between the loan officers who compile the credit score and the bank headquarters.

Agarwal and Hauswald (2010) analyze the credit score building process of a large US bank specialized in small business lending. In this bank, loan officers assigned to loan applications originate an initial credit score based on hard information, "codified" soft information drawn from interviews with borrowers, and "uncodified" information by upgrading loans whose ex ante score is in the grey zone (they don't, however, make a distinction between codified and uncodified in their analysis). In this framework, Agarwal and Hauswald (2010) find that the likelihood of delegating real authority - in the form of asking for more soft information and deferring credit decisions to local loan officers - increases with the hierarchical distance. In contrast to Agarwal and Hauswald (2010), delegation is fixed in our bank and is not a choice variable for senior management. More importantly, we separately analyze the codified and uncodified discretion channels and the role of hierarchical distance in the deployment of each.

Our findings also contribute to the literature on bank organization and soft information production and lending relationships. Consistently, a number of studies document that more hierarchical banks (or branches at a greater distance from the bank headquarters) produce and use less soft information (Scott, 2004; Berger et al., 2005; Uchida et al., 2012; Ogura and Uchida, 2014; Liberti, 2018, Skrastins and Vig, 2018) and shy away from small business lending and soft-information-based credit relationships (Mian, 2006; Detragiache et al., 2008; DeYoung et al., 2008; Alessandrini et al., 2009, 2010; Presbitero and Zazzaro, 2011; Fiordelisi et al., 2014; Lee and Brown, 2017; Filomeni et al., 2020). More closely related to our research, Liberti and Mian (2009) analyze loans to large corporate customers made by a multinational bank in Argentina and find that the sensitivity of the approved loan amount to subjective, soft information declines as the geographical distance between the loan officer managing the loan application and the higher-ranked bank officer with the responsibility for the final lending decision increases, while sensitivity to objective, hard information is significantly higher for loans approved at a higher hierarchical distance. Qian et al. (2015) study the relation between communications costs and information production in a large Chinese bank, confirming the importance of "human touch" and socio-cultural proximity in communication. Namely, they find that internal ratings have more power to predict default when the loan officer and the branch manager have worked together professionally for a longer period and have had the opportunity to know and trust each other. Finally, Levine et al. (2019) find that the introduction of new airlines routes reducing travel time (and allegedly communication costs) between bank headquarters and branch counties determines an increase of small business lending in the branch's county, consistent with Stein's (2002) model of the transmission of soft information across a bank's hierarchy.

In this paper, we add to this line of research by studying in a granular way the impact that communication frictions in hierarchical banks have on origination and use of internal credit ratings.

3. The bank lending environment

We study the credit scoring and lending decisions of the lead bank of a large multinational European banking group, with total assets of 646 billion euros, a total market capitalization of about 50 billion euros and subsidiaries in twelve central-eastern European and Mediterranean countries. In the home country, the group has 14 affiliated banks and about 4,500 branches covering a market share of about 15% in the loan and deposit markets. In particular, the lead bank (the data provider) operates in the home country (to which data refer) with about 1,900 traditional branches located in 16 regions.

The Corporate and Investment Banking Division (CIB) of our data provider, which is responsible for mid-corporate loan applications, is structured in 24 corporate branches spread out over the home country in 12 different regions. These corporate branches reflect an organizational structure that separates mid-corporate banking from the retail banking activity associated with small firms and households at traditional branches. Loan officers at CIB branches take charge of the loan applicants from the very beginning of the lending process, generating the credit score rating and submitting the loan proposal to the relevant authority within the bank's hierarchy. Officer compensation includes, besides a fixed salary, a discretionary component that is based on the volume of loans generated by the loan officer. Specifically, each year loan officers are assigned a personal loan target in order to access minimum extra bonuses. Loan volumes above the target are then associated with greater bonuses. Furthermore, loan officer's activities and rating override proposals are closely monitored at the bank's headquarters where the officer's career prospects ultimately depend on the overall assessment by bank's risk management officers. Given such compensation and assessment schemes loan officers may have an incentive to inflate credit ratings, to increase the number and aggregate size of their approved loans. At the same time, they are also aware that the overall approval success and the subsequent performance of loans whose financial score were inflated or overridden by them are similarly important for career advancement. In this vein, excessive rating inflation might have a negative effect on the ability of a loan officer to get her loans approved and expose him/her to reputational losses.

3.1. Credit score formation

The bank uses a semi-automated credit scoring system in which the final rating attributed to a borrower depends on quantitative (hard) and qualitative (soft) information produced by the local loan officer in charge of the loan application. The final rating varies from 1 to 15, where the fifteenth rating class is the riskiest and is equivalent to an S&P rating of CCC. Figure 1 provides a graphical representation of the credit score building process at our bank.

[Insert Figure 1 about here]

The credit scoring process is initiated by a loan officer at the CIB local branch to which the company applies. Loan officers are assigned to new applications randomly, according to a queueing system, while loan renewals tend to be assigned to the loan officer who originated the first score. When a loan officer starts the scoring process, the rating system of the bank automatically generates a "statistical rating" component, which reflects the probability of default exclusively based on quantitative information extracted from the firm's financial statement. Next the credit scoring system incorporates current hard performance information on the applicant firm using data drawn from the credit registry at the Central Bank plus private hard information drawn from the bank's own portfolio database. This second step generates a "modified statistical rating", which can deviate (upwards or downwards) from, or be equal to, the statistical rating.

After the scoring algorithm has produced this modified statistical rating, the loan officer completes a qualitative questionnaire, which gives the opportunity to inject his/her subjective judgment about several business and market characteristics. These characteristics include the riskiness of the applicant's business, the positioning strategy of the company in the market, its future investment projects, its financial position, its management quality, ownership and organizational structure (see the Appendix). While this subjective assessment is limited to the choice of a specific option in a set of predefined options, the actual pieces of information (the input) used by the loan officer in completing the qualitative questionnaire are broadly unobservable by other agents at the bank. The answers by loan officers to each specific question are quantified into a numerical score and enter the borrower's credit score through a proprietary algorithm of the bank. The output of this process is an *"integrated rating"*, reflecting the modified statistical rating possibly corrected by a notching factor based on the loan officer's subjective assessment of the applicant reflected in the qualitative questionnaire. Loan officers at our bank do not know the exact weighting rule used by the rating model to combine quantitative and qualitative information into an integrated rating. However, they have the chance to test several input parameters before the integrated rating is ultimately saved and processed by the system. This gives loan officers the opportunity to adjust their qualitative assessment iteratively in order to affect the integrated rating. Therefore, any deviation of the integrated rating from the modified statistical rating reflects the exercise of discretion by the local loan officer. We refer to this type of discretion as codified discretion because the nature of the soft information injected by the loan officer at this stage is framed by the bank in a standardizable and codifiable numerical scale, because it is mandatory on the part of loan officer, because it is not associated with any qualitative justification by the loan officer, and it is not subject to any validation procedure by senior bank managers.

At the end of the credit scoring process, the loan officer has the opportunity to override the integrated rating and propose a *"final rating"* that can either confirm or deviate from the integrated rating. Overrides of (i.e., deviations from) the integrated rating are closely monitored at the bank headquarters. When overriding a borrower's rating, the loan officer has to provide a written motivation to the upper layer of the bank (i.e., the *Rating Unit*). Rating deviations may encompass one or more rating notches that lead to either upgrades or downgrades of the integrated rating. Reasons for a downward override range from commercial risks stemming from deterioration in the economic conditions in which the firm operates to marketing strategies not adequately defined or even to regulatory changes that can compromise the value of the firm. Reasons for upgrades in the rating are related to factors that mitigate the applicant's credit risk such as penetration into markets with strong socio-economic development opportunities and expanding demand, participation in projects with strong creditworthy partners, or ongoing restructuring projects aimed at a reduction of the cost structure or a capital increase (see the Appendix II for some examples excerpted from upgrade and downgrade override notes kindly provided us by the bank). All these reasons fit well with the notion of "pure" soft information as the set of unverifiable *"opinions, ideas, rumors, economic projections, statements of management's future plans, and market commentary"* (Liberti and Petersen, 2019, p. 4) that are gathered, processed and assessed by the figure of the loan officer located at the local branch, and communicated to senior managers at the bank's headquarters in the form of text. Sometimes, however, override notes may include a reassessment of (hard) financial statements based on the soft information available to the loan officer or news about (hard) accounting data which are not yet reflected in the borrower's balance sheet and cannot be captured by the present statistical rating. Unfortunately, the bank has only provided us with a few excerpts from both upgrade and downgrade override notes. This prevents us from carrying out textual analysis on override notes to distinguish these different types of soft information hardening.

That said, whatever the reasons for the override decision, they are assumed by the bank to be non-codifiable into specific categorical statements and not quantifiable into a well-specified objective metric. Instead, they can only be communicated within the banking organization by detailed explanatory notes. We refer to this type of non-mandatory subjective assessment of loan applications as uncodified discretion. Our separate analysis of uncodified discretion (i.e., overrides) and codified discretion allows for distinctions among different types of soft information "hardening" and for the possibility that some types of (initially) soft information might be more amenable to "hardening" than others and/or more likely to be manipulated.

3.2. Credit score communication

From the moment that the loan officer finishes the credit score building process, he/she cannot modify his/her appraisal anymore. At that point, the credit score generated by the loan officer (together with the credit file and all the information that went into making the rating) can be sent higher up in the bank's hierarchy where adjustments to the score might occur. Precisely, scores that contain an upward override of the integrated rating are communicated to the specialized *Rating Unit* located at the bank's headquarters for approval[2]. In contrast, downward overrides are approved automatically by the system and the score is directly passed to the bank manager who approves the loan. In any case, however, written notes produced by the loan officer are exposed to inspections by the loan reviewers at the bank's headquarters with possible reputational ramifications that could affect his/her career prospects.

A second potential check point within the bank's hierarchy associated with the communication of the credit score is the bank manager who has loan approval authority. The hierarchical design of our bank involves eleven levels of approval at which the bank manager with loan approval authority might reside. The first level coincides with the loan officer originating the credit score (approval level 1). The highest level where approving managers might reside is at the executive board (approval level 11). In the first nine hierarchical levels of approval a single bank manager has decision making authority, whereas in the last two hierarchical levels the designated loan approving authority is a committee.[3] The location of the loan decision-maker varies with the level of approval. At the second hierarchical level the manager receiving the credit score and making the ultimate decision about the

---

[2] From credit files, we can observe approved rating overrides, but we do not observe override proposals that are rejected by the Rating Unit.

[3] The hierarchical level of approval is determined by a set of applicant and loan characteristics specified in the bank's credit policy manuals. The rules specifying approval delegation take into account the total exposure of the banking organization to the applicant company (or, in case of subsidiary corporations, to the economic group to which the applicant company belongs), the amount of credit for which the company applies, the applicant's credit score and the strength of credit risk mitigation in the form of collateral and personal guarantees.

loan approval resides in the same branch as the loan officer originating the credit score, thus minimizing problems of information transmission and facilitating the use of soft information. At the third and fourth level of approval the bank officer with the loan approving authority may be located in the same branch as the originating loan officer (i.e., the loan appraiser) or may be situated elsewhere in one of the seven regional departments of the bank. From the fifth level of approval on, the ultimate loan decision-maker is located at the headquarters of the bank. For loans approved at the levels 2-4, the credit file moves directly to the bank manager with approval authority. For loans approved by the fifth level onwards, the credit file first moves to the Credit Division for a non-binding opinion and then reaches the deliberative officer/board. The loan officer originating the credit rating knows who will be making the approval decision when he/she finalizes his/her work on the credit file and the loan rating. Table 1 reports the distribution of our sample applicants according to the hierarchical level of approval and the hierarchical distance from the ultimate bank officer approving the loan. In particular, the indicator variable *Same branch* takes the value 1 if the loan officer and the ultimate approving officer are located in the same branch, and zero otherwise.

[Insert Table 1 about here]

Our tests for the hardening of soft information focus on the geographical distance between the officer originating the credit score and the bank's headquarters (hereafter for brevity "BHD"), where the credit scores are communicated and exposed to review at the Rating Unit and Credit Division, where the loan officer's reputational capital is at risk and his/her career trajectories and annual bonuses are determined. To take into account other possible organizational frictions related to the distribution loan approval authority within the bank, which can have an influence on the discretionary decision of loan officers to harden soft information in the credit score, we also control for the hierarchical level of approval. Finally, to test for the reliability of information hardened and transmitted in the credit score we also consider the distance between the officer responsible for reviewing the loan application and the officer responsible for the loan approval ("BHD_2").

[Insert Figure 2 about here]

4. Data, models and variables

4.1. Dataset

The data used in this study have been manually collected from the credit folders of all (550) mid-corporate loan applications managed (either eventually approved or denied) by the Corporate and Investment Banking Division of a major European bank from September 2011 to September 2012. The mid-corporate segment comprises firms having annual turnover between 150 million and 1 billion euros. This segment of the loan market is typically less plagued by problems of information opaqueness than SMEs. For this reason, lending to the mid-corporate segment should be less vulnerable to problems of information transmission across bank organizational structure. This likely biases us against finding an impact of distance (i.e., against finding frictions in the transmission of information) on credit scoring and lending decisions.

Each credit folder contains very granular information on the credit scoring process including the final and all intermediate scores. In addition, each folder contains detailed information on applicant and loan characteristics, on the identity and location of the loan officer in charge of the application and the hierarchical level at which the loan is ultimately approved (or denied).

4.2. Estimated models for loan officer discretion

The first issue we address is whether and how communication frictions related to *BHD* affects the use of discretion by loan officers and the ability/willingness to harden soft information in the credit scoring process successfully. Unfortunately, we do not observe the soft information to which loan officers have access, and the non-use of discretion by loan officers does not imply that they did not collect and use soft information. It is possible that soft information available to loan officers is consistent with the hard information employed in the underwriting process. That is, it is possible that the appropriate credit score for the applicant is exactly equal to his/her financial modified statistical rating. However, we can reasonably assume that the likelihood that the soft information generated by the loan officer confirms the hard information employed in the credit score building process (and, therefore the likelihood that loan officers find it appropriate to keep the rating produced by the automated scoring algorithm) should not vary systematically with their distance from the bank headquarters. Under this assumption, a statistically significant impact of *BHD* on the use of discretion would reveal the existence of communication frictions within the banking organization. The empirical model for loan officer discretion is:

$$Discretion_i = f[c + \alpha BHD_i + \sum_j \beta_j (Loan\ Officer\ Characteristics)_{ji} + \sum_h \gamma_h (Loan\ Characteristics)_{hi} + \sum_k \delta_k (Firm\ Characteristics)_{ki} + D_{area} + D_{industry} + \varepsilon_i] \quad (1)$$

where the subscript *i* indicates the loan application and the loan officer originating the credit score.

As a first step, we estimate the likelihood of loan officers using subjective discretion in the credit scoring process. To this end we use two indicator variables. In line with Brown et al. (2012) and Gropp and Guettler (2018), *discretion_1* assumes the value of 1 if the *final rating* is different from the *modified statistical rating* produced by the scoring algorithm on the basis of pure hard information and 0 otherwise. However, *discretion_1* does not distinguish between the case of non-use of the discretion by the loan officer, in which *final rating* = *integrated rating* = *modified statistical rating*, from that of a double use of both codified and uncodified discretion which counterbalance each other, in which (*final rating* - *integrated rating*) = - (*integrated rating* - *modified statistical rating*) leaving the final rating equal to the statistical rating. Therefore, we build another indicator variable, i.e., *discretion_2*, which takes the value of 1 when both the integrated rating is different from the modified statistical rating and the final rating is different from the integrated rating.[4]

Second, we consider *codified discretion* and *uncodified discretion* separately to discriminate between the decision to harden and transmit codifiable and uncondifiable soft information. In this case, *codified discretion* is a dummy variable assuming value 1 if a loan officer generates an *integrated rating* different from *modified statistical rating*, while *uncodified discretion* is a dummy assuming value 1 if the if the loan officer exercises discretion by overriding the *integrated rating* and transmitting a higher or lower *final rating*.

Third, we analyze the probability that loan officers use their discretion to improve or worsen the credit rating of the applicant. In this regard we estimate a multinomial logit model in which *codified discretion_12* and *uncodified discretion_12* are categorical variables that assume the value zero if loan officers do not use discretion, the value 1 if loan officers downgrade the applicant's rating, and the value 2 if loan officers upgrade the applicant's rating:

---

[4] In unreported regressions, we also use *discretion_3* that takes the value of 1 if *integrated rating* $\neq$ *modified statistical rating* or if the *final rating* $\neq$ *integrated rating*. Estimation results, available upon request, are qualitatively the same to the ones we obtain with *discretion_1* and *discretion_2*.

$$\text{CODIFIED\_DISCRETION\_012} = \begin{cases} 2 & \text{if integrated rating < modified statistical rating (upgrade)} \\ 1 & \text{if integrated rating > modified statistical rating (downgrade)} \\ 0 & \text{if integrated rating = modified statistical rating} \end{cases}$$

$$\text{UNCODIFIED\_DISCRETION\_012} = \begin{cases} 2 & \text{if final rating < integrated rating (upgrade)} \\ 1 & \text{if final rating > integrated rating (downgrade)} \\ 0 & \text{if final rating = integrated rating} \end{cases}$$

As the rating adjustment has no natural ordering, we use multinomial logistic regressions to estimate the likelihood of loan officers choosing one of the three discretionary options. We assume that each loan officer attaches a random utility $U_{iz} = x'_{iz}\beta + \varepsilon_{iz}$ to the alternatives z = 0, 1, 2 of confirming, upgrading, or downgrading the rating of the applicant. In this case, the likelihood of the loan officer choosing alternative z is equal to the likelihood of this alternative yielding the maximum utility among all the other alternatives, $\text{Prob}(\textit{Discretion\_012} = z) = \text{Prob}\left(x'_{iz}\beta + \varepsilon_{jz} > x'_{iz'}\beta + \varepsilon_{iz'}\right)$ for any $z' \neq z$. For minimizing computational problems, we assume that the random terms ε_{iz} are independent and identically distributed with log-Weibull distribution and estimate the following multinomial logit model (Greene, 2012):

$$\text{Prob}(\textit{Discretion}\_012 = z) = \frac{\exp(x'_{iz}\beta)}{\exp(x'_{i0}\beta)+\exp(x'_{i1}\beta)+\exp(x'_{i2}\beta)} \tag{2}$$

As Equation (2) makes it clear, the independence of ε_{iz} is equivalent to assuming the odds ratio $\text{Prob}(\textit{Discretion\_012} = z)/\text{Prob}(\textit{Discretion\_012} = z')$ to be independent of the excluded alternative. For the type of decision that we analyze, i.e., whether to exercise discretion on the basis of soft information produced by loan officers, the assumption of independence of irrelevant alternatives (the IIA property) does not appear to be very restrictive. Loan officers decide whether to adjust or recommend an adjustment of the applicant's rating on the basis of the kind of soft information that they have produced and the associated communication problems that they have to face. Hence, when they produce favorable (unfavorable) information about the applicant what is really at stake is the option to adjust the rating upwards (downwards) versus confirming the automated score produced by the model.

For robustness, we also rerun all regressions using a multinomial probit model, which does not assume the IIA property and where the error terms ε_{ij} are assumed to follow a multivariate normal distribution and be correlated across choices. Although in some cases we have to use slightly different model specifications to overcome convergence problems, the results are both qualitatively and quantitatively indistinguishable from that of multinomial logit regressions.[5]

Table 2 reports the definition of the dependent and explanatory variables used in the analysis and their descriptive statistics. In 44% of the loan applications loan officers changed the modified statistical rating that was based on just pure hard information. In 36% of the cases loan officers introduce subjective elements into the credit scoring process by "hardening" soft information into the numerical scale provided by the qualitative questionnaire on the applicants' characteristics *(codified discretion)*: out of these changes, 41% are upgraded and 39% downgraded. In 19% of the loan applications the loan officers "harden" soft information by overriding the *integrated rating* using *uncodified discretion.* As we noted above, this is augmented with detailed explanatory notes to senior managers. In 69% of these cases an upgrade was recommended, and in 31% a downgrade. Moreover, in 6.5% of the loan applications loan officers make use of both *codified* and *uncodified discretion.*

To the extent that hard information can be transmitted unimpeded at distance through the bank's organization without loss of content, our hypothesis is that if soft information can be successfully hardened in the credit score, then the use of codified and uncodified discretion by loan officers responsible for the scoring process should be unaffected by their geographical position in the bank's organization. Therefore, if α is non-significantly different from zero, then the use of discretion by loan officers in the formation of the credit scoring would not be affected by frictions in communicating and transferring codifiable and/or uncodifiable soft information at a distance within the bank's organization. In contrast, statistically significant coefficients for *BHD* indicate the existence of internal communication frictions that influence systematically the use of soft information by loan officers. If $\alpha < 0$, loan officers in remote branches are discouraged from injecting soft information in the credit scoring process presumably in anticipation of reputational and career risks associated with communicating this information to senior officers and loan reviewers that are culturally and physically very distant. On the contrary, $\alpha > 0$ indicates that loan officers at distant branches are more likely to use their subjective knowledge to adjust the statistical and/or integrated scores, possibly to increase the probability of loan approval and generate an extra performance bonus (see footnote 3). Finally, negative coefficients for distance variables in the

[5] For reasons of space, results are unreported and available from the authors upon request.

uncodified discretion model and positive coefficients in the *codified discretion* model would indicate that communication problems within the bank organization push loan officers at peripheral branches to prefer hardening their soft information in codified responses to standard questionnaire items instead of hardening it for transmission in its least quantifiable form of written notes supporting rating override requests.

Our cross-applicant analysis could potentially suffer from selection and omitted variables problems, such that one cannot take our findings as conclusive evidence of the impact of distance and within-organization communication frictions on the use of soft information in credit-scored lending. To the extent that applicants choose the branch to which they apply, the match between an applicant firm and the branch where the credit scoring is conducted could be related to unobserved firm risk factors and other characteristics that may affect the use of soft information by loan officers.[6] Similarly, the personnel policy followed by the bank could be such that loan officers at the peripheral branches are systematically different from those at the branches closest to bank headquarters, and these individual characteristics could be correlated with the attitude to use discretion in the credit score building process. If so, estimated coefficients on *BHD* would simply capture the fact that the characteristics of borrowers and/or loan officers at distant branches tend to motivate a lesser or greater use of soft information. In order to mitigate (even if not entirely eliminate) this concern we include a large number of control variables for loan officer, firm and loan characteristics and fixed effects for unobserved characteristics at the regional and industry level. This provides reasonable justification for our assumption that *BHD* is almost randomly assigned conditional on observables, and allows us to interpret results as capturing the fundamental relationship between communication frictions within a banking organization and the discretionary injection of soft information in credit scoring by loan officers[7].

4.3. Estimated model for time to lending decision

Besides inhibiting the hardening of soft information by loan officers at a distance from the bank headquarters, frictions in communication across bank hierarchical layers can also affect the

---

[6] It is worth noting that for 75% of borrowing firms in our sample (80% if stand-alone firms), the branch of the bank to which they apply for a loan is the one closest to their headquarters. That said, our regressions control for the distance between the branch responsible for the credit score and the headquarters of applicant firm.

[7] To the extent that riskier firms are arguably more likely to apply to peripheral branches and that higher applicant risk is positively associated with the probability of rating downgrades and negatively with the probability of rating upgrades, our results overestimate the impact of distance (and communication frictions) on the discretionary use of positive soft information and underestimate the effects on the use of negative soft information.

perceived reliability of the credit scores originated at peripheral branches. In this vein, we explore whether, the *final rating* being equal, the time that elapses between the completion of the credit score by the loan officer reviewing the loan application at the local branch and the final decision by the official approving the loan varies with the organizational distance, i.e. *time to lending. Time to lending* is measured as the number of days between the date in which the credit score is submitted and the date in which the bank manager responsible for the loan approval makes the final decision. It reflects the effort put by the bank's loan approving authority to reach the final lending decision and depends on the confidence assigned to the final rating submitted by the loan officer responsible for the loan application (Paravisini and Schoar, 2013). As our response variable *time to lending* is an over-dispersed count variable with the conditional variance exceeding the conditional mean, a negative binomial model for modelling *time to lending* is appropriate.[8] Precisely, we estimate the following negative binomial model:[9]

$$Time\ to\ Lending_i = f[c + \alpha_1 Organizational\ distance_i + \alpha_2 Organizational\ distance_i \times Final\ Rating_i + \gamma_1 Final\ Rating_i + \gamma_2 Final\ Rating_i^2 + \textstyle\sum_j \beta_j\,(Loan\ Officer\ Char)_{ji} + \sum_h \gamma_h\,(Loan\ Char)_{hi} + \sum_k \delta_k\,(Firm\ Char)_{hi} + D_{area} + D_{ind} + \varepsilon_i] \quad (3)$$

The inclusion of both *final rating* and its square captures possible inverted U effects of applicants' risk on *time to lending*, such that loan applications from very good and very bad applicants are easily and promptly decided by the bank's managers with approval authority.

The variable *organizational distance* is measured, alternatively, by the branch-to-headquarters distance *(BHD)* and by the geographical distance between the the branch where the loan officer who originates the credit score resides and the branch of the bank officer with approval authority *(BHD_2)*. As displayed in figure 2, *BHD_2* is equal to zero for loans approved at the same branch of the loan officers who originate the score, it is a positive number for loans deliberated at the regional departments, and it coincides with BHD for loans deliberated at the bank headquarters[10].

[8] Negative binomial regression can be considered as a generalization of Poisson regression since it has the same mean structure as Poisson regression and it has an extra parameter to model the over-dispersion. Negative binomial regression coefficients are interpreted as follows: for a one unit change in the predictor variable, the difference in the logs of expected counts of the response variable is expected to change by the respective regression coefficient, given the other explanatory variables in the model held constant.

[9] We also run the same empirical model shown in Equation (3) by using a linear probability model and results remain qualitatively unchanged, as shown in Table 6.

[10] Correlation between *BHD* and *BHD_2* is 0.41.

On the one hand, an estimated coefficient α_1 significantly greater than zero associated with the main effect of *Organizational distance* indicates the presence of communication frictions that do not allow the information hardened in the credit score to travel within the banking organization without loss of content. On the other hand, an estimated coefficient α_2 significantly greater than zero associated with the interaction term *Organizational distance* × *Final rating* takes into account the possibility that the reliability assigned to credit scores originated at distant branches depends on the level of the applicant's final rating submitted by the local loan officer. In particular, if local loan officers are thought to have an incentive to inflate credit ratings, "gaming" the system in order to increase the number and volume of approved loans, we should expect that the effect on *time to lending* is stronger for the good applicants who receive a low credit score (i.e., low probability of default).

4.4. Estimated models for loan performance

The final rating is an inverse measure of the borrower's creditworthiness that measures the likelihood that borrowers may trigger a negative credit event such as bankruptcy, loan default, or payments that are missed, partial, or late. Communication frictions between loan officers responsible for assessing the credit quality of loan applications and senior managers at the bank's headquarters responsible for reviewing those applications, and loan officers' discretionary decisions to harden soft information may affect loan performance and the loan distress predictive power of the final rating.

Therefore, the final rating being equal, we explore whether (i) the probability of loan distress varies with the spatial distance between the loan officer responsible for the formation of the credit score and the bank's headquarters; (ii) the ways in which loan officers harden soft information by using codified and uncodified discretion affect loan performance; (iii) the possible effects of the discretionary use of soft information on the bank's likelihood of experiencing negative credit events vary with the branch-to-headquarters distance. To this purpose, we estimate the following logit models, whose full specifications are:

$$Loan\ distress_i = f\big[c + \alpha_1 BHD_i + \alpha_2 Fin\ Rating_i + \alpha_3 BHD_i \times Fin\ Rating_i + \textstyle\sum_j \beta_j\,(Loan\ Officer\ Char)_{ji} + \sum_h \gamma_h\,(Loan\ Char)_{hi} + \sum_k \delta_k\,(Firm\ Char)_{hi} + D_{area} + D_{ind} + \varepsilon_i\big] \tag{4}$$

and

$$Loan\ distress_i = f[c + \alpha_1 BHD_i + \alpha_2 Fin\ Rating_i + +\alpha_3 BHD_i \times Fin\ Rating_i + \alpha_4 Discretion\ up_i + \alpha_5 BHD_i \times Discretion\ up_i + \alpha_6 Discretion\ down_i + \alpha_7 BHD_i \times Discretion\ down_i + \sum_j \beta_j\ (Loan\ Officer\ Char)_{ji} + \sum_h \gamma_h\ (Loan\ Char)_{hi} + \sum_k \delta_k\ (Firm\ Char)_{hi} + D_{area} + D_{ind} + \varepsilon_i] \quad (5)$$

where *Loan distress* is a dummy that takes the value of 1 if the loan either becomes past due, unlikely-to-pay, forborne or non-performing, and 0 otherwise.

In model (4), the coefficient α_1 captures the impact of possible communication frictions linked to branch-to-headquarters distance on the likelihood of occurrence of negative credit events, while the coefficient α_3 indicates that communication frictions lead loan officers to a more (if $\alpha_3 < 0$) or less (if $\alpha_3 > 0$) cautious assessment of applicants' credit risk. In model (5), the coefficients α_4 and α_6 indicate whether, the final rating being equal, the incorporation of soft information in the credit scoring process by loan officers contributes to predicting loan performance, by distinguishing between positive and negative soft information hardening, while the coefficients α_5 and α_7 highlight whether this possible contribution is homogeneous across branches or varies with the spatial distance between local branches and the bank's headquarters.

4.5. Explanatory variables

4.5.1. Organizational distance

Our key organizational distance variable is *BHD*. It is measured as the logarithm of 1 plus the physical distance in kilometers between the branch in which the loan officer responsible for the credit score operates and the bank's main headquarters. *BHD* reflects communication frictions due to the spatial separation and lack of personal contact, cultural affinity common languages and mutual trust between loan officers at local branches and senior managers at the bank's headquarters that may inhibit the hardening and transmission of soft information within the banking organization.[11] In our sample, the average branch-to-headquarters distance is 290.2 kilometers, with the distance varying between 2.5 and 1,482 kilometers.

[11] It is possible that branch-to-headquarters distance reflects differences in business culture that do not derive from the spatial distance between the communicating parties. Specifically, they could capture differences in business culture that arise from the acquisition of branches from other banks. However, because none of the corporate branches of our bank were the consequence of M&A deals, and because the loan underwriting process is uniform across our organization, we can reasonably assume that loan officers at these branches share the same corporate culture independent of their location and that the major (or the only) sources of exogenous variation in communication frictions within the bank are the two organizational distances.

The second organizational distance variable*, BHD_2,* is computed as the logarithm of 1 plus the kilometric distance between the branch of the loan officer originating the credit score and the branch of the bank manager(s) with approval authority. The average value of this second organizational distance is 150.6 kilometers, varying from 0 (when the loan is deliberated at the same branch of the loan officer originating the credit score) to 1,576 kilometers (when approval decisions are made at the bank headquarters).

4.5.2. Ways to harden soft information

In model (5) we test whether and how hardening soft information affects the informational power of the final rating in predicting the probability of loan distress. To this end we first consider two indicator variables, i.e., *Discretion up* and *Discretion down*, that take the value of 1 if the loan officer uses their discretion to harden soft information to override the integrated rating or to adjust the modified statistical rating through the qualitative questionnaire upwards or downwards, respectively.[12] Second, we distinguish the ways in which soft information is hardened by constructing the additional binary variables *Uncodified up* and *Uncodified down* that take the value of 1 when loan officers override the integrated rating by communicating uncodifiable soft information in their override notes, and *Codified up* and *Codified down*, that take the value of 1 when loan officers adjust the modified statistical rating by injecting their codifiable soft information in the qualitative questionnaire.[13]

In our sample, 13% and 6% of integrated ratings are overridden by loan officers upwards and downwards respectively, through the transmission of written motivations to senior managers located at the bank's headquarters, while 15% and 21% of modified statistical ratings are adjusted by loan officers upwards and downwards, respectively, through the mandatory qualitative questionnaire that has to be filed by the loan officer.

4.5.3. Control variables

With regard to loan officer characteristics, we control for gender with the indicator variable *gender* taking the value 1 if the loan officer is male. Our sample contains individual data on 122 different loan officers belonging to 24 CIB branches, 78% of which are males. Psychological, sociological and

---

[12] Formally: (i) *Discretion up* = 1 if *final rating* $<$ *integrated rating* or *integrated rating* $<$ *modified statistical rating* and 0 otherwise; (ii) *Discretion down* = 1 if *final rating* $>$ *integrated rating* or *integrated rating* $>$ *modified statistical rating* and 0 otherwise;

[13] Formally: (i) *Uncodified up* = 1 if *final rating* $<$ *integrated rating* and 0 otherwise; (ii) *Uncodified down* = 1 if *final rating* $>$ *integrated rating* and 0 otherwise; (iii) *Codified up* = 1 if *integrated rating* $<$ *modified statistical rating* and 0 otherwise; (iv) *Codified down* = 1 if *integrated rating* $>$ *modified statistical rating* and 0 otherwise.

economic studies indicate that women are usually more risk averse and less overconfident than men (see Croson and Gneezy (2009)), and have lower job mobility due to different societal roles and gender-based discrimination at the company and labor market levels (see Loprest (1992), Fuller (2008), and Del Bono and Vuri (2011)). Women tend to be less selfish and competitive (see Buser et al. (2014)) and more selfless and supportive than men (see Eckel and Grossman (1998), (2001), and Dufwenberg and Muren (2006)). These differences were found to influence loan officer behavior in loan origination, risk taking and lending relationships (see Bellucci et al. (2010), Agarwal and Ben-David (2014), and Beck et al. (2013))[14]. On the one hand, greater risk-aversion, lower self-confidence and career concerns may discourage female loan officers from using soft information and exercising discretion, especially uncodified discretion. On the other hand, greater female social-orientation and trust building capacity could have opposite, and possibly asymmetric, effects on the use of discretion for upgrading and downgrading applicant firms' scores.

We also control for loan officer age *(age)* and job tenure *(experience)*. The average loan officer in our bank is 49 years old, with 21 years on the job: *age* varies from 20 to 60 years, while *experience* ranges from 1 to 37 years. Extant evidence on the influence of these variables on lending decisions is mixed. Agarwal and Wang (2009) and Agarwal and Ben-David (2014) document that older and more experienced loan officers have a higher loan approval rate and their loans have a higher probability of defaulting, suggesting that risk aversion and career concerns are strongest at the beginning of their career. By contrast Beck et al. (2013) find that loans underwritten and monitored by older officers have a lower probability of turning problematic, while Qian et al. (2015) find that loan officer's experience has no significant effect on loan prices and ex-post performance. Therefore, the expected impact of *age* and *experience* on the use of discretion is also *a priori* ambiguous.[15]

From credit folders we draw a number of loan and firm characteristics that could have an impact on the use of discretion by loan officers. We consider five variables that could capture the degree of accessibility and transmissibility of soft information and the existence of agency problems. The first is *repeated lending,* which is an indicator variable distinguishing between applicants with an existing or past lending relationship with the bank (value 1) and new applicants (value 0). The second variable, *scope of relationship,* captures the breadth of the bank-firm relationship: it is dummy

[14] For a comprehensive overview of the literature looking at the impact of the loan officer gender on bank-firm relationships see Bellucci et al. (2011).

[15] *Age* and *Experience* can suffer from collinearity (in our sample correlation between the two variables is 0.55). To assuage multicollinearity concerns, in unreported regressions available upon request, we have estimated model (1) by separately including *Age* and *Experience*. Results are qualitatively the same as the ones we obtain when we estimate a specification with both *Age* and *Experience*.

that assumes the value 1 if the borrower purchases at least one additional product/service from the bank besides the loan, and 0 otherwise. Third, we consider the logarithm of 1 plus the distance between the branch where the loan officer works and the headquarters of the applicant company *(branch-to-borrower distance),* which recent banking literature views as reducing information asymmetries and monitoring costs (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Bellucci et. al., 2013). Fourth, we control for the distribution of loan approval authority within the banking organization in terms of the hierarchical level *(approval level).* This allows us to control for possible additional communication and organizational frictions with managers using the credit score for the lending decision. Moreover, to the extent that delegation of loan approval authority is related to specific characteristics of loan applications and multiple hierarchical levels are located in the same branch/headquarters, this allows us to isolate the impact of information transmission problems related to physical distances between communicating parties.

Finally, each folder contains information about potential bank management conflicts of interest arising in lending decisions. In particular, we build the indicator variable *related lending,* which assumes the value of 1 for loans characterized by the presence of a conflict of interest and 0 otherwise.[16]

We also control for a set of borrower and loan characteristics reflecting the firm's financial health and information transparency. First, we control for the *modified statistical rating* and *integrated rating* in the equations for *codified discretion* and *uncodified discretion,* respectively. Second, we include applicant firm size measured by the logarithm of total assets *(total assets).* Third, we include the binary variables *collateral* and *global guarantee,* the former assuming the value 1 if the credit line is collateralized, and 0 otherwise, and the latter being equal to 1 if the credit line is backed by a guarantee of the parent company. In addition, we control for whether the firm is part of group *(group belonging).* Finally, all regressions include four geographical area and industry dummies to control for unobserved characteristics of local credit market and credit demand that could be correlated with our distance measures. In the discretion model we do not include branch dummies because they largely reflect the effects of distance from the bank headquarters. However, standard errors are clustered at the branch level to allow for heteroskedasticity and possible correlation of the error term

[16] According to regulation in the bank's home country, bank representatives are barred from involvement in financial contracts (e.g., commercial loans) with companies in which they retain a substantial interest. This prohibition can only be overcome by a unanimous vote of the bank's management board and the unanimous vote of the company's board of directors. For example, *related lending* refers to interlocking directorships, where a bank representative sits at the same time on the management board of the bank and on the board of directors of the borrowing firm, or substantial stock ownership in a customer enterprise, reflecting a potential conflict of interest.

within each branch due to some branch specificity. In the model for time to lending decision we also estimate specifications with branch dummies.

5. Results

5.1. Hardening soft information

In table 3 we report in columns (1)-(4) the results for the likelihood of loan officers using discretion in the credit scoring process. As we stated, *discretion_1* (columns (1) and (2)) captures the probability of observing a final rating different from the automated (hard information-based) modified statistical rating, independently of the underlying type of discretion used by the loan officer, i.e., codified or uncodified. In columns (3) and (4), *discretion_2* takes into account the possibility of a simultaneous use of codified and uncodified discretion that leads the final rating to be equal to the modified statistical rating (actually, in our sample this happens in seven cases).

Results of both linear probability and logistic regressions show that the coefficient on *BHD* is not statistically different from zero: the probability of loan officers exercising discretion by adjusting the statistical rating automatically produced by the credit scoring system is statistically independent of the distance from the bank's headquarters. This result is arguably consistent with the hypothesis that credit scoring technologies make communication frictions within the bank hierarchy negligible.

Variables that significantly influence the use of discretion are the age of the loan officer and the hierarchical level at which the loan is approved. Consistent with the hypothesis that younger loan officers are less risk averse, we find that *age* has a negative impact on *discretion_1:* a thirty-eight year old loan officer (corresponding to the 10th percentile of *age* distribution) is 23 percentage points (p.p.) more likely to exercise discretion than a fifty-six year old loan officer (at the 90th percentile (58% versus 35%)).[17] If we compare loans approved by the loan officer him/herself *(approval level* = 1) with those approved at the bank's headquarters level *(approval level* = 11) we find that the disparity in the likelihood of the final rating recommended by loan officers being different from the modified statistical rating is even greater, 36% versus 60%. Thus, contrary to the findings in Agarwal and Hauswald (2010), formal delegation of contract-approving power leads loan officers to rely more strongly on hard information in generating the final rating, i.e., delegation discourages loan officers from making an explicit use of discretion through subjective score adjustments based on soft-information elements. Finally, as expected, for loan applications with a potential conflict of interest,

[17] The impact of explanatory variables on the probability of loan officers exercising discretion is computed using the "margins" command in Stata, keeping all the other variables at the average.

the probability of loan officer adjusting the automated statistical rating is significantly lower than that of non-related loan applications.

In columns (1)-(4) of table 4 we split *discretion_1* into *codified discretion* and *uncodified discretion*. In using *codified discretion,* the loan officer may adjust the statistical rating, which is produced automatically by the scoring algorithm on the basis of hard financial statements, by incorporating his/her subjective knowledge of the applicant into codified responses to questionnaire questions. In using *uncodified discretion*, the loan officer may propose a final adjustment of the applicant's score by communicating pure, non-codifiable soft information in the form of written notes attached to his/her rating override request.

The apparent insignificant impact of *BHD* on the exercise of loan officer discretion in hardening soft information hides separate (and opposite) effects for the two types of soft information input, *codified* and *uncodified.* Moving from the 10th to the 90th percentile of the *BHD* distribution the probability of loan officers deploying *codified discretion* increases from 22.7% to 43.7% (for loan officers at the median distant branch the probability of exercising *codified discretion* is 35.3%). In contrast, the probability of loan officers overriding the *integrated rating* by communicating their subjective knowledge by submitting specific notes on the given applicant decreases from 22.5% to 4% (for loan officers at the median distance from the bank's headquarters the probability of exercising *uncodified discretion* is 7.8%).

Multinomial regression results in table 5 confirm that the distance from the bank's headquarters has an influence on the decision of injecting subjective soft information into the credit score, and that the impact on *codified discretion* is the opposite to that on *uncodified discretion* In addition, the direction of the score adjustment is not equally affected by *BHD*. Loan officers at hierarchically distant branches are found to be significantly more likely to upgrade the modified statistical score of applicants by submitting high-score answers to the questionnaire's questions relative to hierarchically close loan officers (specifically, 15.7% for loan officers at the 90th percentile of the *BHD* distribution, 6.3% for those at the median, and 1.1% for those at the 10th percentile), while the probability of downgrading is statistically unaffected by the distance from the bank's headquarters. In contrast, *BHD* has a decreasing impact on the likelihood of downward overrides[18], such that for a

[18] The effect of BHD on upward overrides is negative but not statistically significant at the standard levels. This may not be surprising if we consider that upgrades have to be approved by the *Rating Unit* and we do not observe rejected proposals. Thus, the greater tendency of loan officers who are closer to the bank's headquarters to propose upward overrides could be hidden by the higher number of proposals that were rejected by the *Rating Unit*.

loan officer at the 90th percentile of the *BHD* distribution the choice of not downgrading is almost certain (97.4%), while it is 95.8% at the median and 90.4% at the 10th percentile.

These results do not reject the possibility that some soft information may be hardened in the form of codified discretion. But, the evidence also suggests that credit scoring technologies cannot eliminate the communication frictions within the banking organization, and that the "hardening" of soft information by loan officers in the form of codified and uncodified discretion is influenced by how distant they are from the bank's headquarters. Loan officers who are located remotely from the bank's headquarters are reluctant to inject bad or good soft information when the type of soft information cannot be standardized into responses to codified questions, while tend to increase the modified statistical rating. That is, they are less likely to transmit pure, non-codifiable soft information to higher levels in the bank hierarchy relative to loan officers in branches close to the bank's headquarters, but more likely to inject good codifiable soft information into the system. Taken together, these results are consistent with hierarchically distant loan officers having an incentive to inflate the statistical rating of their applicants by hardening the type of soft information that is less likely to be scrutinized and reversed by senior managers at the bank headquarters, because it is incorporated in answers to well-defined and codified questions included in a mandatory questionnaire (Berg et al., 2013; Brown et al., 2015; Mosk, 2014).

Moving on control variables, the age of loan officers discourages them from exercising discretion regardless of the type of soft information, codifiable or non-codifiable. By contrast, the duration of job tenure *(experience)* seems to have effect only on the decision to exercise *uncodified discretion*, in particular, on the probability of downgrading the *integrated rating.*

The type of lending relationship *(scope of relationship* and *repeated lending)* does not have significant effects on *codified discretion* and *uncodified discretion,* while the existence of a possible conflict of interest between the borrower and the lender *(related lending)* brings to zero the probability of loan officers adjusting the statistical rating of the applicant upwards either via the questionnaire or recommending an override of the integrated rating.

Further, it is interesting to note that loan officers are more likely to inflate the statistical rating of large firms and less likely to downgrade it: moving from the 10th to the 90th percentile of the firm assets distribution, the probability to exercise *codified discretion* upwards goes from 1% to 18.7%, while it goes from 25.4% to 12.4% for downwards adjustments. However, the size of the applicant has only a small and slightly significant influence on the decision to exercise non-codified discretion upward. Once again, this finding confirms that loan officers tend to adjust upwards the score of large customers by inflating answers to the questionnaire which are unlikely to be corrected at the approval stage.

Finally, an interesting difference between *codified discretion* and *uncodified discretion* is that only the former seems to have the implicit-insurance content against interest rate fluctuations suggested by Brown et al. (2012), as loan officers are more (less) likely to adjust upwards (downwards) the rating of risky applicants having a high modified statistical rating.

5.1.1. Delegation of authority

The delegation of approval authority to loan officers may affect their incentives to exercise discretion and communicate soft information. On the one hand, loan officers with the formal authority to make the final lending decision may have a greater incentive to acquire soft information (Aghion and Tirole, 1997), and hence could be in a better position to exercise discretion in producing credit scores. On the other hand, they may have a lower incentive to explicitly adjust the applicant's financial score recommending a different rating to the bank's upper layers (Dessein, 2002). Recent findings by Bouwens and Kroos (2012) and Agarwal and Hauswald (2010) indicate that loan officers to whom loan approval authority is delegated have a lower tendency to inflate the automated scores of their applicants.

In order to investigate the effects of authority delegation on the use of discretion, we include a dummy variable *delegation* that assumes the value of 1 for loans approved by loan officers responsible for the credit scoring process (i.e., loans assigned to the approval level 1) and 0 otherwise, and an interaction term between *delegation* and *BHD*. The results are reported in table 6, panel a. First, the delegation of authority has an impact only on *codified discretion*, while it does not affect the loan officers' decision to override and transmit "pure" soft information to the upper hierarchical levels. Second, consistent with theoretical predictions in the literature on authority delegation, the negative coefficient on the interaction indicates that loan officers that are functionally close to the bank's headquarters, and hence suffer less from information asymmetries and communication frictions within the banking organization, are more likely to exercise *codified discretion* when they are responsible for loan approval. In contrast, loan officers that are hierarchically distant from the bank's headquarters are less prone to use *codified discretion* if they have the power to approve the loan. In particular, as shown in figure 2 (panels a and b), for loan officers located at the 10th percentile of *BHD* distribution the probability of adjusting the automated statistical rating of applicants is 15.4% if the decision on the loan approval rests with other bank managers and 33.5% if they have the power to approve the loan. For loan officers located at the 90th percentile of *BHD* the two probabilities are instead 51.6% and 27.5%, respectively. The impact of *delegation* on the decisions to deflate or inflate the automated statistical rating is qualitatively the same, even if its magnitude is greater for the latter, while the mitigating impact of *BHD x delegation* (the interaction term) is greater both in magnitude and statistical significance on the decision to upgrade the applicant's statistical score as shown in figure 2 (panels c and d).[19] Once again, these results are consistent with the hypothesis that loan officers make discretionary adjustments to credit scores in order to increase the probability of loan approval.

5.1.2. Additional controls

In table 6 we include three additional control variables capturing information transparency and the financial strength of applicant firms. Specifically, we control for: (i) the share of long-term debt over the total assets of the company *(long term debt),* to capture greater stability of financing sources and, to the extent that long-term debt includes traded bonds, greater information disclosure, (ii) the share of intangible assets over total assets *(intangible assets),* to reflect information opacity, and (iii) the ratio of equity over total assets *(equity ratio),* to reflect financial risk.

Although, due to missing values, the number of observations decreases considerably, the results are robust to the inclusion of these additional controls. On the whole, they have a statistically significant influence only on *uncodified discretion.* Unsurprisingly *long term debt* and the *equity ratio* increase the likelihood of loan officers overriding the integrated score, while *intangible assets* has a negative impact on the use of discretion. Importantly, the estimated coefficients on *BHD* keep their sign and statistical significance. This confirms that loan officers operating in branches at a distance from the bank's headquarters tend to adjust applicants' scores by communicating soft information via codified responses to a standardized questionnaire, while they are reluctant to communicate positive or negative soft information about applicants when this information has to be transmitted by means of detailed, specific notes.

[19] Specifically, loan officers with approval power are less likely to deflate the credit score than loan officers without approval power already at the 25th percentile of *BHD* distribution (15.6% versus 17.3%) and at the 75th percentile the difference is 8.3 percentage points (13.2% versus 21.6%). For the probability to exercise discretion upwards, loan officers at the 25th percentile of *BHD* are more likely to inflate the automated modified statistical rating if they have the approval power (4.5% versus 3.2%); by contrast, loan officers at the 75th percentile of *BHD* with loan approval delegation have 7% probability of inflating the applicant's score against 10.3% of loan officers without approval power.

5.2. Time to lending decision

In investigating the use of discretion by the bank's loan officers, our main finding is that the use of both codified and uncodified discretion varies with the distance between the branch in which the loan officer operates and the bank's headquarters. This is consistent with frictions in the process of communicating information from the loan officer to the upper layers of the bank's hierarchy that can ultimately lead to misguided and inaccurate lending decisions. In such a context, the final rating commonly used by banks' managers to evaluate a given borrower can be not perfectly informative, thus casting doubts on its reliability within the bank organization and delaying loan approval. This gets exacerbated by the incentive of loan officers to inflate borrowers' credit ratings with the objective to increase lending volumes which ultimately lead to the achievement of greater bonuses.

Estimation results for the effects of *final rating* and *organizational distance* variables *(BHD* and *BHD_2)* on *time to lending* are reported in Table 7. In columns (1) to (5) we use a negative binomial model for the number of days from the submission of the final rating to the approval decision; in columns (6) to (10) we use an OLS model for the logarithm of 1 plus the number of days to the approval decision.

As expected, *final rating* has a positive and concave effect on *time to lending* that is overall statistically significant across specifications. This suggests that the bank's manager called to make a decision on loan approval takes little time and effort when the applicant's expected default is very low, while time effort to decision grow less than proportionally to the final rating.

Moving on to the organizational distance variables, the time taken to decide on a given loan application systematically varies with both the geographical distances between the loan officer responsible for originating the applicant's credit scoring and the bank's headquarters *(BHD),* and between the loan officer and the bank's branch with the loan approval authority *(BHD_2)*. Specifically, the average number of elapsed days between the submission of the applicant's folder and credit score by the local loan officer and the final lending decision increases with the organizational distance from the bank's decisional centres. However, the negative coefficient on the interaction terms *BHD* × *final rating* and *BHD_2* × *final rating* indicates that the incremental effects of *BHD* and *BHD_2* are significantly lower when the final rating is high, that is when the credit scoring originated by the local loan officer indicates that the applicant is a high default-risk borrower. By contrast, when loan officers at distant branches submit low final ratings by presenting the applicants as very safe the application folders are very thoroughly scrutinized and the final lending decisions take a greater extra time.

Concerning the economic impact of *BHD* and *BHD_2* we find that moving from the 10th to the 90th percentile of their distributions the average number of days to decision increases, respectively, by 12 and 20 days for the safest applicants (*final rating* = 1), while it decreases by about 4 days or remains the same for the applicants with *final rating* = 15.[20]

The significant effects of organizational distances on *time to lending* reflect the existence of communication frictions in bank organizations. In particular, they are consistent with the hypothesis that geographically-distant loan officers have incentives to inflate borrowers' final ratings to increase the probability of loan approval. Therefore, senior managers at bank headquarters being aware of this inflative tendency pay especially great attention to loan applications with good credit scores submitted by loan officers at distant branches.

5.3. Loan performance

So far, we have found that communication frictions within the banking organization affect the decision of loan officers who are at a distance from the bank's headquarters on whether and how to harden soft information in the credit scoring process. We now address the following questions related to loan performance: Do the bank-to-headquarters distance or the incorporation of hardened soft information in the final rating affect loan performance? Do they condition the predictive power of the final rating in forecasting the occurrence of a negative credit event?

Table 8 reports estimation results of models (4) and (5) for the likelihood of the loan experiencing financial distress by becoming past due, unlikely-to-pay, forborne or non-performing in the two years after the loan has been disbursed. First, let us note that, as expected, *Final rating* is the most significant predictor of the loan distress probability with a positive estimated coefficient in all specifications. With regard to the spatial distance of the local branches from the bank's headquarters, we find that, on average, it is not statistically significantly associated with the probability of the bank experiencing a negative credit event (column (1) of table 8). However, when we interact *BHD* with *Final rating* (column (2) of table 8) we find that borrowers rated as "risky" by loan officers located at a distance from the bank's headquarters are less likely to default on payments than borrowers scored by loan officers located at branches close to the bank's headquarters, while the opposite happens for borrowers rated as "safe". Precisely, the predicted probabilities of loan

[20] The impact of explanatory variables on the number of days taken by the bank's approving authority to decide on a given loan application is computed using the "margins" command in Stata for specifications in columns (2) and (4) of Table 6, keeping all the other variables at the average.

distress for an applicant with a final rating equal to 12 evaluated at the 10th and 90th percentile of *BHD* distribution are 0.64 and 0.45, respectively. By contrast, for borrowers rated 4 (resp., 8) the probabilities of loan distress at the 10th and 90th percentiles of *BHD* distribution are 0.002 (resp., 0.05) and 0.05 (resp., 0.18), respectively.[21]

Columns (3)-(6) of table 8 report estimation results of model (5). First, in columns (3) and (4) we test whether, for two firms with the same final rating, the probability of loan distress is different according to whether the final rating reflects only hard information available to the bank or whether it incorporates soft information generated by loan officers at local branches. In this regard, we find that, by keeping the final rating constant, loans that incorporate positive and negative soft information are, respectively, less and more likely to experience repayment problems, even if only the coefficient on *Discretion up* is statistically significant. Precisely, for loans rated 8 and 12 the probability of distress decreases by, respectively, 8.6 and 28.9 p.p., while for safe borrowers the reduction is economically and statistically close to zero. These effects do not vary significantly with the spatial distance between the local branches and the bank's headquarters. Second, in columns (5) and (6), we consider whether the ways in which soft information is hardened matter. On the one hand, when we consider the ways in which soft information is hardened, i.e., column (5), we find that only the use of uncodifiable soft information has an effect on the likelihood of loan distress that adds to that of the final rating. In particular, the estimated coefficients on both *Uncodified up* and *Uncodified down* increase their magnitude and significance as *BHD* increases. On the other hand, when we investigate whether the effect of hardening soft information on loan distress is homogeneous across branches or varies with the spatial distance between local branches and the bank's headquarters, i.e., column (6), we show that final ratings that incorporate a positive override are 3 p.p. less likely to default when the loan officer responsible for the applications operates at a local branch which is at the 10th percentile of *BHD* distribution and this variation is statistically non-significant. By contrast, when we move to the 90th percentile of *BHD* distribution we find that upwards overrides reduce the probability of loan distress by, on average, 16.6 p.p. and that this effect is statistically significantly. On the other hand, our findings suggest that the incorporation of negative soft information in the final rating decreases the probability of loan distress only for downwards override proposed by loan officers at a distance from the bank's headquarters (i.e., at the

[21] Again, the impact of explanatory variables on the probability of loan distress is computed using the "margins" command in Stata, keeping all the control variables at the average values. In the case of specifications (3)-(6), when we calculate the impact of each ways of hardening soft information on the loan performance, we keep the indicators for the other ways of hardening soft information at zero.

90th percentile of *BHD* distribution, on average, the probability of loan distress is 96.2% when *Uncodified down* is equal to 1, and 16.7% when *Uncodified down* is equal to zero). Overall, our findings on the ways to harden soft information confirm the cautious attitude of loan officers operating at distant branches in incorporating soft information in the credit scoring process. Indeed, loan officers located at distant branches harden soft information by overriding integrated ratings only when it is so revealing of the applicant's creditworthiness that it overcomes the frictions that hinder the unbiased communication of soft information along the bank's hierarchy. By contrast, the discretionary use of soft information by loan officers operating at branches close to the bank's headquarters does not affect the average distress probability of loans placed in the same rating class.

6. Conclusions

Information production lies at the heart of the modern theory of the banking firm. A considerable subset of the literature on financial intermediation has focused on the importance of soft information and relationship-building. Both theoretical and empirical work on soft information has emphasized the problematic nature of communicating soft information within the hierarchical structure of banking organizations (Stein, 2002; Berger et al., 2005). At the same time researchers have hypothesized that technological innovation may have enabled banks to "harden" soft information (Berger, 2015; Udell, 2015; Liberti and Petersen, 2017). In this paper, we investigate the extent to which soft information can be "hardened" as part of the credit scoring process and transmitted at distance within hierarchical banks. The issue is important because the extent to which soft information can be hardened will determine the degree to which large complex banks can compete with smaller banks in offering relationship building.

We explore the boundaries of soft information by exploiting a proprietary dataset from a large European bank containing granular loan-level information on credit score formation on a sample of medium- and large-size commercial loan applications. During the loan underwriting process our bank's credit scoring system, like those of many other banks, allows for the injection of soft information at multiple points in the process – in our bank's case, two levels (i.e., stages of the credit score formation process). At the first level, loan officers are required to opine on specific, predetermined relevant dimensions/characteristics of the firm and its management. At the second level, the underwriting loan officer has the option of "overriding" what otherwise would be the final credit score that contains hard information and the soft information from the first injection. This override is not based on expressing opinions on a set of pre-specified dimensions and thus could be viewed as a "purer" form of uncodifiable soft information.

Our tests center on the information frictions produced by communicating at distance. If credit scoring does eliminate communication frictions within the banking organization and soft information can be successfully hardened and transmitted across the banking hierarchy, then we should expect that the discretionary use of soft information is not affected by the geographical distance between the originating loan officer and the bank's headquarters where loan officer proposals are assessed and reviewed.

Summarizing, our results indicate that hardening soft information through the credit scoring technology has its limits. That is, credit scoring does not eliminate the barriers to an unbiased communication of soft information across bank's hierarchy. Specifically, we find that branch-to-headquarter distance matters and affects the propensity of loan officers to use their discretion to inject soft information into the credit score. Interestingly, we also find a distinction between soft information injected by completing a pre-codified qualitative questionnaire on borrower characteristics, and the purer form of soft information involved in the override decision. Loan officers in branches far from the bank's headquarters are likely to inflate the credit score by injecting positive soft information about borrower characteristics in the scoring algorithm through the answers to the qualitative questionnaire required by the bank. In contrast, distant loan officers are less likely to override the integrated rating, both upwards and downwards, by transmitting within the hierarchy the purer form of soft information. Taken together, these findings seem to suggest that loan officers at distant branches tend to exercise discretionary adjustments of automated scores to increase the probability of loan approval, while they shy away from transmitting subjective notes on applicants that are monitored and scrutinized at the bank's headquarters and may have effects on their reputation and career prospects. Both the communication frictions generated by organizational distance and the risk of an inflated-score bias by loan officers operating at peripheral branches are also consistent with our findings on the time span of the loan approval process and on loan performance. On the one hand, the number of days consumed in making the final lending decisions is significantly higher for the loan applications reviewed at distant branches and receiving a good final rating. On the other hand, the final rating being equal, the hardening of soft information through upwards and downwards override decisions of loan officers located at distant branches affects loan performance by, respectively, decreasing and increasing the probability of the bank experiencing a negative credit event.

References

Agarwal, S., R. Hauswald, 2010. "Authority and Information". Working Paper.

Agarwal, S., F. H. Wang, 2009. "Perverse Incentives at the Banks? Evidence from a Natural Experiment". *Federal Reserve Bank of Chicago Working Paper Series*, WP-09-08.

Agarwal, S., I. Ben-David, 2014. "Do Loan Officers' Incentives Lead to Lax Lending Standards?". *NBER Working Papers No.* 19945.

Aghion, P., J. Tirole, 1997. "Formal and Real Authority in Organizations". *Journal of Political Economy* 105(1), 1-29.

Akhavein, J., W. S. Frame, L. J. White, 2005. "The Diffusion of Financial Innovations: An Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations". *Journal of Business* 78(2), 577-596.

Albareto, G., M. Benvenuti, S. Mocetti, M. Pagnini. P. Rossi, 2011. "The Organization of Lending and the Use of Credit Scoring Techniques in Italian Banks". *Journal of Financial Transformation* 32, 143-168.

Alessandrini, P., A. F. Presbitero, A. Zazzaro, 2009. "Banks, Distances and Firms' Financing Constraints". *Review of Finance* 13(2), 261-307.

Alessandrini, P., A. F. Presbitero, A. Zazzaro, 2010. "Bank Size or Distance: What Hampers Innovation Adoption by SMEs?". *Journal of Economic Geography* 10(6), 845-881.

Basel Committee on Banking Supervision (BCBS), 2000. "Range of Practice in Banks' Internal Ratings Systems". *BCBS Discussion Paper*.

Basel Committee on Banking Supervision (BCBS), 2005. "Studies on the Validation of Internal Rating Systems". *BCBS Working Paper No. 14*.

Beck, T., P. Behr, A. Guettler, 2013. "Gender and Banking: Are Women Better Loan Officers?". *Review of Finance*, 17(4), 1279-1321.

Bellucci, A., A. Borisov, A. Zazzaro, 2010. "Does Gender Matter in Bank-Firm Relationships? Evidence from Small Business Lending". *Journal of Banking & Finance* 34(12), 2968-2984.

Bellucci, A., A. Borisov, A. Zazzaro, 2011. "Do Male and Female Loan Officers Differ in Small Business Lending? A Review of the Literature". In G. Calcagnini and I. Favaretto (eds.), *The Economics of Small Businesses: An International Perspective*, New York: Springer, 195-219.

Bellucci, A., A. Borisov, A. Zazzaro, 2013. "Do banks price discriminate spatially? Evidence from small business lending in local credit markets". *Journal of Banking & Finance* 37(11), 4183-4197.

Berg, T., M. Puri, J. Rocholl, 2013. "Loan officer incentives and the limits of hard information". *NBER Working Paper No. 19051*.

Berger, A. N., 2015. "Small Business Lending by Banks: Lending Technologies and the Effects of Banking Industry Consolidation and Technological Change". In A. N. Berger, P. Molyneux and J. O. S. Wilson (eds), *The Oxford Handbook of Banking*, 2nd ed, Oxford Handbooks in Finance, Oxford University Press, pp 292–311.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, J.C. Stein, 2005. "Does function follow organizational form? Evidence from the lending practices of large and small banks". *Journal of Financial Economics* 76(2), 237-269.

Bloom, N., L. Garicano, R. Sadun, J. Van Reenen, 2014. "The Distinct Effects of Information Technology and Communication Technology on Firm Organization". *Management Science* 60(12), 2859-2885.

Bouwens, J., P. Kroos, 2012. "The Effect of Organizational Hierarchy on Loan Rates and Risk Assessments". Working Paper.

Brown, M., M. Schaller, S. Westerfeld, M. Heusler, 2012. "Information or Insurance? On the Role of Loan Officer Discretion in Credit Assessment". *MoFiR Working Paper No. 67*.

Brown, M., M. Schaller, S. Westerfeld, M. Heusler, 2015. "Internal Control and Strategic Communication within Firms - Evidence from Bank Lending". *Working Papers on Finance No. 1504*, University of St. Gallen.

Buser, T., M. Niederle, H. Oosterbeek, 2014. "Gender, Competitiveness, and Career Choices". *The Quarterly Journal of Economics* 129(3), 1409-1447.

Campbell, D., 2012. "Employee Selection as a Control System". *Journal of Accounting Research* 50(4), 931-966.

Campbell, D., M. Loumioti, R. Wittenberg-Moerman, 2019. "Making Sense of Soft Information: Interpretation Bias and Loan Quality". *Journal of Accounting and Economics* 68(2-3), 101240.

Crémer, J., L. Garicano, A. Prat, 2007. "Language and the Theory of the Firm". *The Quarterly Journal of Economics* 122(1), 373-407.

Croson, R., U. Gneezy, 2009. "Gender Differences in Preferences". *Journal of Economic Literature* 47(2), 448-474.

Del Bono, E., D. Vuri, 2011. "Job mobility and the gender wage gap in Italy". *Labour Economics* 18(1), 130-142.

Degryse, H., S. Ongena, 2005. "Distance, Lending Relationships, and Competition". *Journal of Finance* 60(1), 231-266.

Degryse, H., J. Liberti, S. Ongena, T. C. Mosk, 2014. "Is Loan Officer Discretion Advised when Viewing Soft Information?". In T. C. Mosk, *Essays on Banking*, Tilburg: CentER, Center for Economic Research.

Dessein, W., 2002. "Authority and Communications in Organizations". *The Review of Economic Studies* 69(4), 811-838.

Detragiache, E., T. Tressel, P. Gupta, 2008. "Foreign Banks in Poor Countries: Theory and Evidence". *Journal of Finance* 63(5), 2123-2160.

DeYoung, R., D. Glennon, P. Nigro, 2008. "Borrower-lender distance, credit scoring, and loan performance: evidence from informational-opaque small business borrowers". *Journal of Financial Intermediation* 17(1), 113-143.

Dufwenberg, M., A. Muren, 2006. "Generosity, Anonymity, Gender". *Journal of Economic Behavior & Organization* 61(1), 42-49.

Eckel, C., P. Grossman, 1998. "Are Women Less Selfish than Men?: Evidence from Dictator Experiment". *The Economic Journal* 108(448), 726-735.

Federal Reserve, 2011. "Supervisory Guidance on Model Risk Management". Board of Governors of the Federal Reserve System, Office of the Comptroller of the Currency, *SR Letter 11-7*.

Fiordelisi, F., S. Monferrà, G. Sampagnaro, 2014. "Relationship lending and credit quality". *Journal of Financial Services Research* 46(3), 295-315.

Filomeni, S., G.F. Udell, A. Zazzaro, 2020. Communication frictions in banking organizations: Evidence from credit score lending. *Economics Letters* 195C, 109412.

Frame, W. S., M. Padhi, L. Woolsey, 2004. "Credit Scoring and the Availability of Small Business Credit in Low- and Moderate-Income Areas". *The Financial Review* 39(1), 35-54.

Fuller, S.,2008. "Job Mobility and Wage Trajectories for Men and Women in the United States". *American Sociological Review* 73(1), 158-183.

Greene, W. H., 2012. "Econometric analysis". New York Pearson Prentice Hall.

Gropp, R., A. Guettler, 2018. "Hidden gems and borrowers with dirty little secrets: Investment in soft information, borrower self-selection and competition". *Journal of Banking & Finance* 87, 26-39.

Levine, R., C. Lin, Q. Peng, W. Xie, 2019. "Communication within Banking Organizations and Small Business Lending". *NBER Working Paper No. 25872*.

Liberti, J. M., A. R. Mian, 2009. "Estimating the Effect of Hierarchies on Information Use". *Review of Financial Studies* 22(10), 4057-4090.

Liberti, J. M., M. A. Petersen, 2019. "Information: Hard and soft". *The Review of Corporate Finance Studies* 8(1), 1-41.

Liberti, J. M., 2017. "Initiative, Incentives, and Soft Information". *Management Science* 64(8), 3469-3970.

Loprest, P., 1992. "Gender Differences in Wage Growth and Job Mobility". *American Economic Review* 82(2), 526–532.

Mian, A. R., 2006. "Distance Constraints: The Limits of Foreign Lending in Poor Economies". *Journal of Finance* 61(3), 1465-1505.

Mocetti, S., M. Pagnini, E. Sette, 2017. "Information Technology and Banking Organization". *Journal of Financial Services Research* 51(3), 313-338.

Mosk, T. C., 2014. "Delegation of Authority and Information Manipulation: Evidence from Bank Lending Decisions". In T. C. Mosk, *Essays in on Banking*, Tilburg: CentER, Center for Economic Research.

Nakamura, L. I., K. Roszbach, 2018. "Credit ratings, private information, and bank monitoring ability". *Journal of Financial Intermediation* 36, 58-73.

Oesterreichische Nationalbank (OeNB), 2004. "Guidelines on Credit Risk Management: Rating Models and Validation". In cooperation with the Financial Market Authority (FMA).

Ogura, Y., H. Uchida, 2014. "Bank Consolidation and Soft Information Acquisition in Small Business Lending". *Journal of Financial Services Research* 45(2), 173-200.

Paravisini, D., A. Schoar, 2013. "The Incentive Effects of Scores: Randomized Evidence from Credit Committees". *NBER Working Paper No. 19303*.

Petersen, M. A., R. G. Rajan, 2002. "Does Distance Still Matter? The Information Revolution in Small Business Lending". *Journal of Finance* 57(6), 2533-2570.

Presbitero, A. F., A. Zazzaro, 2011. "Competition and Relationship Lending: Friends or Foes?". *Journal of Financial Intermediation* 20(3), 387-413.

Puri, M., J. Rocholl, S. Steffen, 2011. "Rules versus Discretion in Bank Lending Decisions". Working Paper.

Qian, J., P. E. Strahan, Z. Yang, 2015. "The Impact of Incentives and Communication Costs on Information Production and Use: Evidence from Bank Lending". *Journal of Finance* 70(4), 1457-1493.

Scott, J. A., 2004. “Small Business and the Value of Community Financial Institutions”. *Journal of Financial Services Research* 25(2-3), 207-230.

Skrastins, J., V. Vig, 2018. “How Organizational Hierarchy Affects Information Production”. *The Review of Financial Studies* 32(2), 564-604.

Stein, J., 2002. “Information Production and Capital Allocation: Decentralized Versus Hierarchical Firms”. *Journal of Finance* 57(5), 1891-1921.

Uchida, H., G. F. Udell, N. Yamori, 2012. “Loan Officers and Relationship Lending to SMEs”. *Journal of Financial Intermediation* 21(1), 97-122.

Udell, G. F., 2015. “SME Access to Intermediated Credit: What Do We Know and What Don't We Know?”. RBA Annual Conference Volume, in: Angus Moore & John Simon (ed.), *Small Business Conditions and Finance*, Reserve Bank of Australia, 61-109.

Figures and tables

Figure 1. The credit scoring process

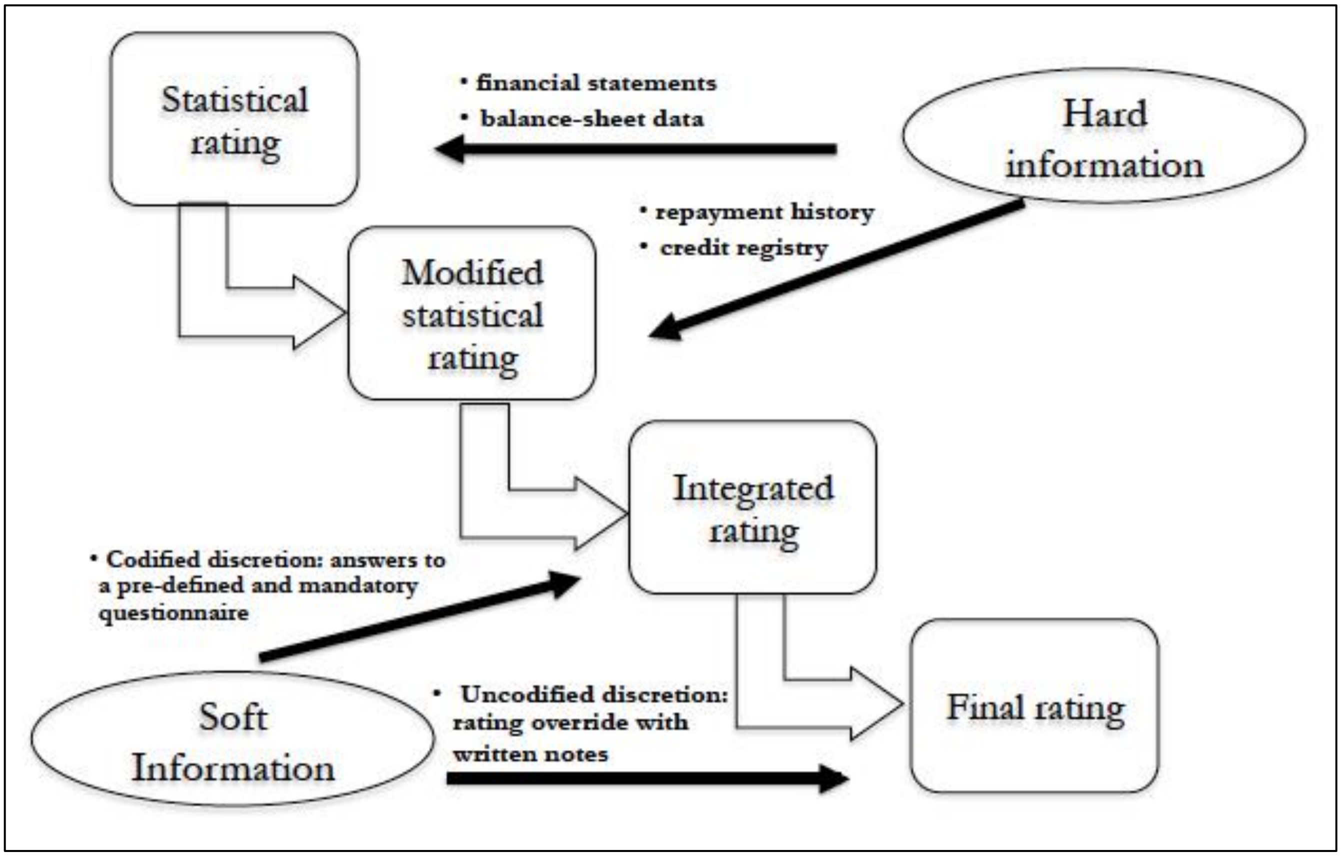


Figure 2. The loan approval process

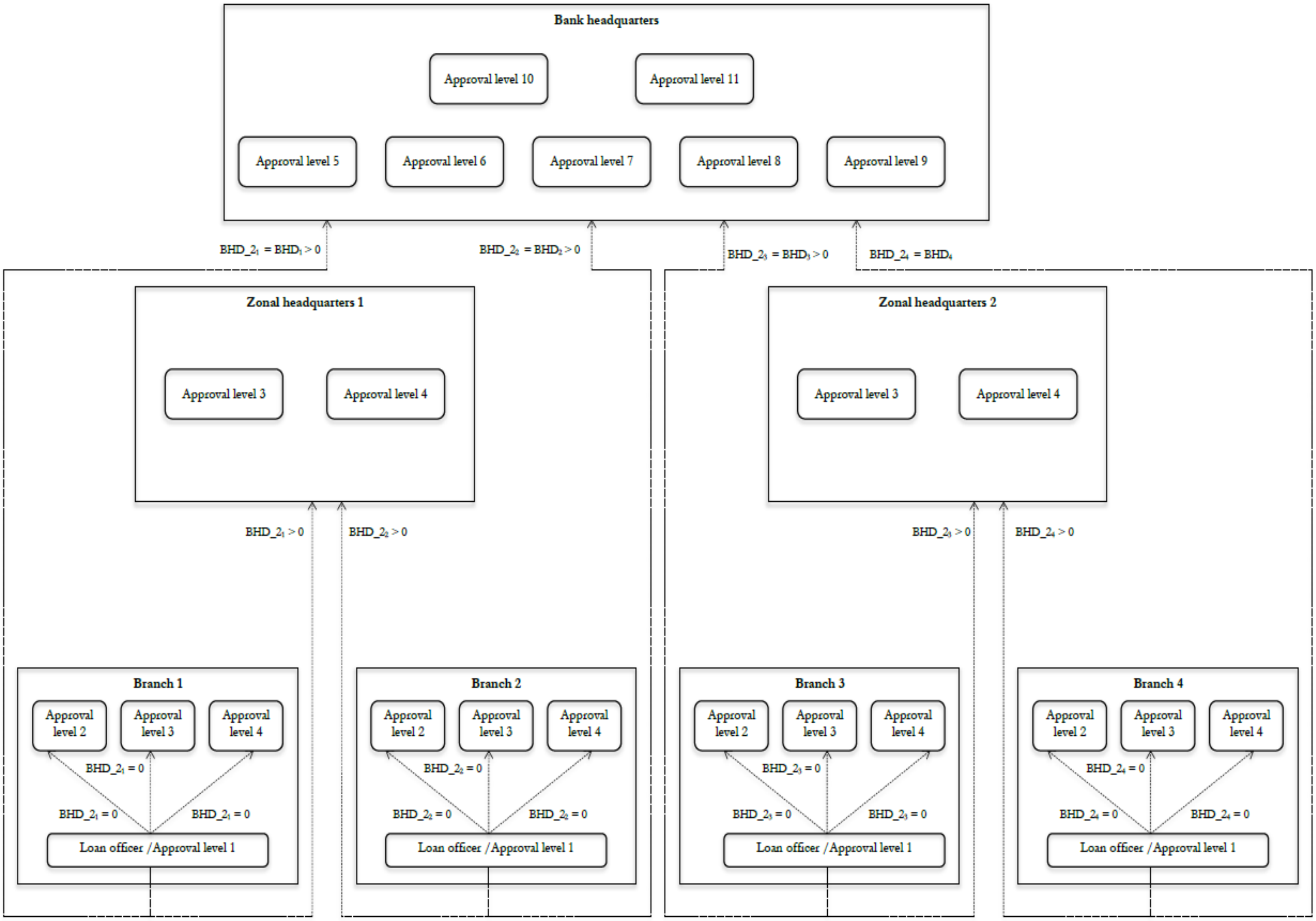
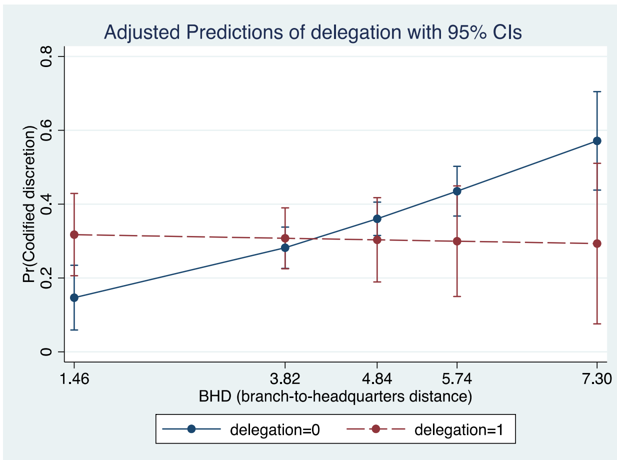
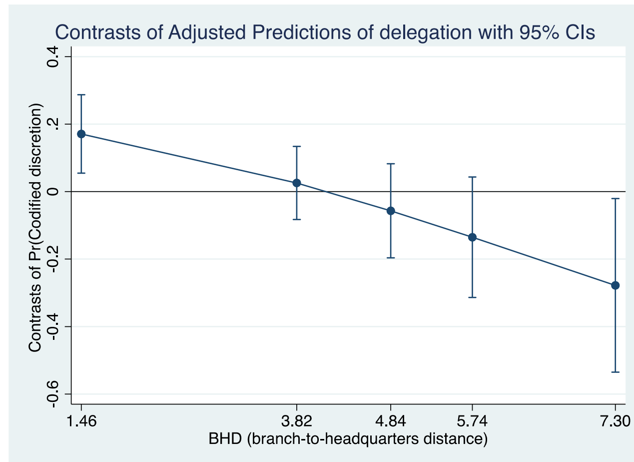


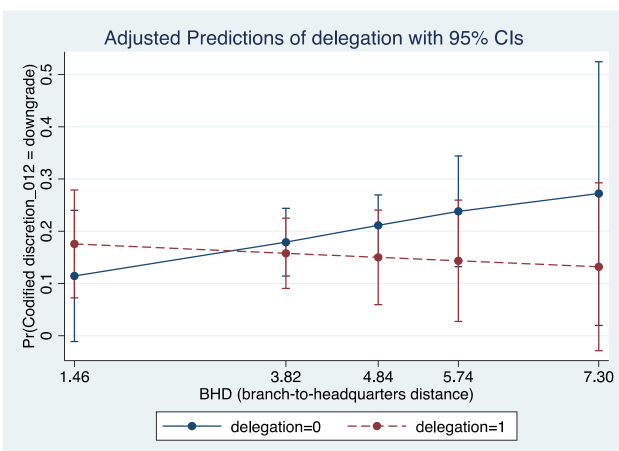
Figure 3. Predicted outcomes of CODIFIED_DISCRETION at percentiles of BHD when loan approving authority is (is not) delegated to loan officers



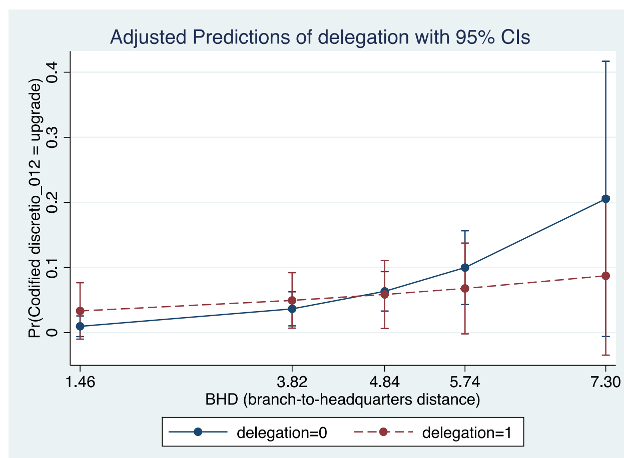
Panel (a): Codified discretion



Panel (b): Contrasts of Codified discretion



Panel (c): Codified discretion: downgrade



Panel (d): Codified discretion: upgrade

Notes: on the x-axis are reported the 10th, 25th, 50th, 75th, and 90th percentiles of *BHD* distribution.

Table 1. Distribution of applicants by approval level

	Level of approval											
	1	2	3	4	5	6	7	8	9	10	11	Total
Same branch 0	0	0	30	91	10	87	16	24	43	14	5	319
1	121	87	17	5	0	0	0	0	0	0	0	231
Total	121	87	47	96	10	87	16	24	43	14	5	550

Table 2. Descriptive Statistics (values expressed in Euro)

Variables	Definition	Obs.	Mean	Std. dev.	Min.	Max.
Dependent variables						
Discretion_1	dummy equal to 1 if modified statistical rating ≠ final rating; 0 otherwise.	464	0.44	(NA)	0	1
Discretion_2	dummy equal to 1 if modified statistical rating ≠ integrated rating, and integrated rating ≠ final rating, and 0 otherwise.	464	0.065	(NA)	0	1
Uncodified discretion	dummy variable equal to 1 if integrated rating ≠ final rating; 0 otherwise.	483	0.19	(NA)	0	1
Codified discretion	dummy equal to 1 if modified statistical rating ≠ integrated rating, 0 otherwise.	464	0.36	(NA)	0	1
*Discretion_012**	step variable equal to 0 if final rating = modified statistical rating; 1 if final rating > modified statistical rating; 2 if final rating < modified statistical rating.	464 [258 110 96]	0.65	(NA)	0	2
*Uncodified discretion_012**	step variable equal to 0 if final rating = integrated; 1 if final rating > integrated rating; 2 if final rating < integrated rating.	483 [393 28 62]	0.32	(NA)	0	2
*Codified discretion_012**	step variable equal to 0 if integrated rating = modified statistical rating; 1 if integrated rating > modified statistical rating; 2 if integrated rating < modified statistical rating.	464 [296 99 69]	0.51	(NA)	0	2
Time to Lending	number of days between the date in which the credit score is submitted and the date in which the bank manager responsible for the loan approval makes the final decision [logarithm of 1 + number of days].	550	16.66 [1.71]	26.9 [1.61]	0 [0]	211 [5.36]
Loan Distress	dummy equal to 1 if the loan becomes past due, unlike-to-pay, forborne or non-performing in the two years after the loan has been disbursed and 0 otherwise.	550	0.23	(NA)	0	1
Discretion-related variables						
Discretion up	dummy equal to 1 if final rating < integrated rating or integrated rating < modified statistical rating and 0 otherwise.	483	0.26	(NA)	0	1
Discretion down	dummy equal to 1 if final rating > integrated rating or integrated rating > modified statistical rating and 0 otherwise.	483	0.25	(NA)	0	1
Uncodified up	dummy equal to 1 if final rating < integrated rating and 0 otherwise.	483	0.13	(NA)	0	1
Uncodified down	dummy equal to 1 if final rating > integrated rating and 0 otherwise.	483	0.06	(NA)	0	1
Codified up	dummy equal to 1 if integrated rating < modified statistical rating and 0 otherwise.	464	0.15	(NA)	0	1
Codified down	dummy equal to 1 if integrated rating > modified statistical rating and 0 otherwise.	464	0.21	(NA)	0	1
Distance-related variables						
BHD	logarithm of 1 + distance in kilometers between the branch in which the loan officer responsible for the credit score operates and the bank's headquarters [km].	550	4.60 [290.2]	1.75 [390.4]	1.25 [2.5]	7.30 [1482]
BHD_2	logarithm of 1 + distance in kilometers between the branch in which the loan officer responsible for the credit score operates and the bank's loan approving authority [km].	550	2.67 [150.6]	2.59 [294.3]	0 [0]	7.36 [1576]

Borrower-to-branch distance	logarithm of 1 + distance between the branch the loan officer responsible for the credit score operates and the headquarters of the applicant company [km].	550	4.39 [795.7]	2.10 [2523.3]	0.18 [0.2]	9.60 [14753]
Firm-bank Relationship Variables						
Approval level	step variable taking values between 1 and 11 according to the hierarchical level with the power of loan approval.	550	4.14	2.76	1	11
Gender	dummy equal to 1 if the loan officer responsible for the credit score is a male.	539	0.78	(NA)	0	1
Age	age in years of the loan officer responsible for the credit score.	520	49	6.14	29	60
Experience	years of experience of the loan officer within the bank.	520	21	7.95	1	37
Global guarantee	dummy equal to 1 if the credit line is backed by a guarantee from the parent company and 0 otherwise.	550	0.15	(NA)	0	1
Collateral	dummy equal to 1 if the credit line is collateralized; 0 otherwise.	550	0.39	(NA)	0	1
Scope of relationship	dummy equal 1 if the borrower purchases at least one other banking product from the bank and 0 otherwise.	550	0.52	(NA)	0	1
Repeated lending	dummy equal to 1 if there is a prior lending relationship and 0 otherwise.	550	0.94	(NA)	0	1
Related lending	dummy equal to 1 if the loan application is disciplined ex the article disciplining conflict of interest within the bank and 0 otherwise.	550	0.02	(NA)	0	1
Group belonging	dummy equal to 1 if the borrower is part of an economic group; 0 if it is a stand-alone company.	550	0.89	(NA)	0	1
Rating variables						
Statistical rating	step variable taking values between 1 and 15, where 1 indicates the highest rating.	481	7.44	3.59	1	15
Modified statistical rating	step variable taking values between 1 and 15, where 1 indicates the highest rating.	464	7.35	3.61	1	15
Integrated rating	step variable taking values between 1 and 15, where 1 indicates the highest rating.	483	7.68	3.40	1	15
Final rating	step variable taking values between 1 and 15, where 1 indicates the highest rating.	516	8.02	3.68	1	15
Borrower-specific variables						
Total assets	logarithm of total assets [million euros].	472	18.01 [195]	1.78 [303]	12.32 [0.224]	21.59 [2370]
Intangible assets	ratio of intangible assets to total assets.	455	0.07	0.11	0	0.62
Long term debt	ratio of long-term debt to total assets.	418	0.15	0.16	0	1.23
Equity ratio	ratio of equity to total assets of the company.	472	0.28	0.21	- 0.63	0.96
Loan-specific variables						
Delegation	dummy equal to 1 for loans approved by loan officers. responsible for the credit scoring process; 0 otherwise	550	0.22	(NA)	0	1

Note: Data are manually collected from our data provider. * In square brackets observations for degree 0, 1 and 2, respectively.

Table 3. LPM and Logit regressions of *Discretion_1* and *Discretion_2*

	Discretion_1		*Discretion_2*	
	LPM (1)	Logit (2)	LPM (3)	Logit (4)
BHD	0.005	0.009	-0.004	-0.102
	(0.025)	(0.105)	(0.012)	(0.353)
Gender	-0.036	-0.107	-0.026	-0.280
	(0.070)	(0.306)	(0.034)	(0.906)
Age	-0.011**	-0.051**	-0.004	-0.132
	(0.005)	(0.023)	(0.003)	(0.100)
Experience	0.003	0.015	0.003*	0.091
	(0.004)	(0.018)	(0.002)	(0.086)
Scope of relationship	-0.105	-0.454	-0.014	-0.110
	(0.069)	(0.316)	(0.027)	(0.567)
Repeated lending	-0.029	-0.169	0.047*	(omitted)
	(0.130)	(0.588)	(0.024)	
Borrower-to-branch distance	0.012	0.059	-0.017	-0.369*
	(0.022)	(0.095)	(0.012)	(0.206)
Approval level	0.020**	0.095**	0.004	0.065
	(0.010)	(0.042)	(0.005)	(0.107)
Related lending	-0.341**	-1.802	-0.047	(omitted)
	(0.162)	(1.178)	(0.028)	
Modified statistical rating	0.010	0.047	0.001	-0.037
	(0.010)	(0.045)	(0.004)	(0.073)
Total assets	0.028	0.133	0.011	0.284*
	(0.018)	(0.085)	(0.007)	(0.162)
Collateral	0.092	0.423	-0.002	-0.095
	(0.065)	(0.293)	(0.023)	(0.564)
Global guarantee	-0.080	-0.419	-0.018	-0.245
	(0.078)	(0.364)	(0.037)	(1.065)
Group belonging	0.072	0.331	-0.018	-0.631
	(0.075)	(0.358)	(0.032)	(0.852)
Observations	433	433	433	433
Area FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared/Pseudo R-squared	0.118	0.088	0.125	0.25

Note: in columns (1)-(2) the dependent variable is *discretion_1,* a binary variable equal to 1 if *final rating* is different from *modified statistical rating* and 0 otherwise. In columns (3)-(4) the dependent variable is *discretion_2,* a binary variable equal to 1 if both *final rating* is different from *integrated rating* and *integrated rating* is different from *modified statistical rating,* and 0 otherwise. All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 4. LPM and Logit regressions of *Codified discretion* and *Uncodified discretion*

	Codified discretion		*Uncodified discretion*	
	LPM (1)	Logit (2)	LPM (3)	Logit (4)
BHD	0.041**	0.183**	-0.041**	-0.365**
	(0.020)	(0.097)	(0.019)	(0.169)
Gender	-0.010	0.001	-0.071	-0.530
	(0.064)	(0.295)	(0.055)	(0.493)
Age	-0.006*	-0.029*	-0.009**	-0.103**
	(0.004)	(0.017)	(0.004)	(0.053)
Experience	-0.002	-0.006	0.008***	0.093**
	(0.004)	(0.019)	(0.003)	(0.040)
Scope of relationship	-0.079	-0.341	-0.043	-0.432
	(0.056)	(0.261)	(0.045)	(0.521)
Repeated lending	-0.024	-0.131	0.055	0.469
	(0.154)	(0.714)	(0.095)	(0.901)
Borrower-to-branch distance	0.004	0.025	-0.014	-0.153
	(0.020)	(0.094)	(0.016)	(0.132)
Approval level	0.016	0.076	0.008	0.078
	(0.011)	(0.049)	(0.008)	(0.071)
Related lending	-0.249	-1.371	-0.142**	(omitted)
	(0.159)	(1.196)	(0.059)	
Modified statistical rating	-0.009	-0.045		
	(0.007)	(0.036)		
Integrated rating			0.023***	0.232***
			(0.007)	(0.063)
Total assets	0.018	0.087	0.026*	0.271*
	(0.019)	(0.090)	(0.015)	(0.167)
Collateral	0.011	0.055	0.087**	0.905**
	(0.073)	(0.346)	(0.041)	(0.370)
Global guarantee	-0.078	-0.415	-0.022	-0.292
	(0.079)	(0.416)	(0.045)	(0.489)
Group belonging	-0.022	-0.116	0.035	0.413
	(0.071)	(0.337)	(0.043)	(0.543)
Observations	433	433	433	433
Area FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared/Pseudo R-squared	0.098	0.072	0.161	0.206

Note: in columns (1)-(2) the dependent variable is *codified discretion,* a binary variable equal to 1 if *integrated rating* is different from *modified statistical rating* and 0 otherwise. In columns (3)-(4) the dependent variable is *uncodified discretion,* a binary variable equal to 1 if *final rating* is different from *integrated rating* and 0 otherwise. All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 5. Multinomial Logit regressions of *Codified discretion* and *Uncodified discretion*

	Codified discretion_012		*Uncodified discretion_012*	
	Down (1)	Up (2)	Down (3)	Up (4)
BHD	0.079	0.544***	-0.764***	-0.257
	(0.165)	(0.181)	(0.259)	(0.212)
Gender	-0.082	0.532	-0.462	-0.314
	(0.404)	(0.639)	(1.207)	(0.885)
Age	0.003	-0.061**	-0.183**	-0.083
	(0.032)	(0.030)	(0.087)	(0.057)
Experience	0.007	-0.045	0.247**	0.053
	(0.026)	(0.030)	(0.098)	(0.039)
Scope of relationship	-0.422	-0.274	-0.466	-0.217
	(0.303)	(0.345)	(0.804)	(0.500)
Repeated lending	-0.304	1.057	1.197	0.520
	(0.691)	(0.820)	(0.941)	(1.024)
Borrower-to-branch distance	0.137	-0.178	-0.130	-0.112
	(0.129)	(0.152)	(0.342)	(0.161)
Approval level	0.088*	0.042	0.187	0.016
	(0.052)	(0.075)	(0.137)	(0.077)
Related lending	-0.786	-13.331***	-15.683***	-15.899***
	(1.539)	(0.616)	(1.269)	(1.179)
Modified statistical rating	-0.179***	0.217***		
	(0.049)	(0.065)		
Integrated rating			0.142	0.279***
			(0.100)	(0.089)
Total assets	-0.148*	0.671***	0.001	0.378*
	(0.084)	(0.225)	(0.229)	(0.219)
Collateral	-0.154	0.409	1.976***	0.549
	(0.422)	(0.389)	(0.621)	(0.449)
Global guarantee	-0.455	-0.151	-1.010	-0.082
	(0.418)	(0.637)	(1.169)	(0.629)
Group belonging	-0.250	0.100	0.290	0.532
	(0.301)	(0.806)	(0.490)	(0.845)
Observations	433	433	433	433
Area FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
R-squared/Pseudo R-squared	0.199	0.199	0.279	0.279

Note: in columns (1)-(2), the dependent variable is *codified discretion_012,* a categorical variable equal to 0 if *integrated rating* is equal to *modified statistical rating,* 1 if the applicant modified statistical rating is adjusted downwards *(integrated rating > modified statistical rating),* and 2 if the applicant modified statistical rating is adjusted upwards *(integrated rating < modified statistical rating).* In columns (3)-(4) the dependent variable is *uncodified discretion_012,* a categorical variable equal to 0 if *final rating* is equal to *integrated rating,* 1 if the applicant integrated rating is adjusted downwards *(final rating > integrated rating),* and 2 if the applicant integrated rating is adjusted upwards *(final rating < integrated rating).* All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 6. Logit and Multinomial Logit regressions of *Codified discretion* and *Uncodified discretion*: extensions

	Panel a: the effects of delegation of approval authority to loan officers					
	Codified discretion			*Uncodified discretion*		
	Logit	Multinomial logit		Logit	Multinomial logit	
		Downgrade	Upgrade		Downgrade	Upgrade
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
BHD	0.333***	0.195	0.679***	-0.357**	-0.756***	-0.264
	(0.111)	(0.195)	(0.238)	(0.179)	(0.303)	(0.206)
Delegation	1.583***	0.941	1.985*	-0.168	-1.084	0.151
	(0.516)	(0.660)	(1.065)	(1.125)	(1.794)	(0.733)
BHD × Delegation	-0.386***	-0.277	-0.438*	0.108	0.196	0.068
	(0.141)	(0.191)	(0.270)	(0.195)	(0.268)	(0.153)
Observations	433	433	433	433	433	433
Controls	YES	YES	YES	YES	YES	YES
Area FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
R2/Pseudo R2	0.078	0.205	0.205	0.203	0.286	0.286

	Panel b: additional controls					
	Codified discretion			*Uncodified discretion*		
	Logit	Multinomial logit		Logit	Multinomial logit	
		Downgrade	Upgrade		Downgrade	Upgrade
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
BHD	0.276***	0.198	0.636***	-0.815***	-1.196***	-0.812***
	(0.096)	(0.152)	(0.186)	(0.164)	(0.404)	(0.236)
Long term debt	0.163	-0.773	0.363	6.270***	3.986**	7.678***
	(1.176)	(1.519)	(1.493)	(1.449)	(1.686)	(2.276)
Intangible assets	0.947	0.525	1.003	-4.916**	-30.591**	-3.245
	(1.162)	(1.899)	(2.115)	(2.426)	(15.217)	(2.438)
Equity ratio	-0.335	1.388	-3.756***	2.513	0.697	3.551
	(0.884)	(1.436)	(1.467)	(2.431)	(2.957)	(2.253)
Observations	379	379	379	379	379	379
Controls	YES	YES	YES	YES	YES	YES
Area FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
R2/Pseudo R2	0.077	0.219	0.219	0.306	0.407	0.407

Note: in columns (1a)-(1b) the dependent variable is *codified discretion,* a binary variable equal to 1 if *integrated rating* is different from *modified statistical rating* and 0 otherwise. In columns (2a)-(2b) and (3a)-(3b), the dependent variable is *codified discretion_012,* a categorical variable equal to 0 if *integrated rating* is equal to *modified statistical rating,* 1 if the applicant modified statistical rating is adjusted downwards *(integrated rating > modified statistical rating),* and 2 if the applicant modified statistical rating is adjusted upwards *(integrated rating < modified statistical rating).* In columns (4a)-(4b) the dependent variable is *uncodified discretion,* a binary variable equal to 1 if *final rating* is different from *integrated rating* and 0 otherwise. In columns (5a)-(5b) and (6a)-(6b), the dependent variable is *uncodified discretion_012,* a categorical variable equal to 0 if *final rating* is equal to *integrated rating,* 1 if the applicant integrated rating is adjusted downwards *(final rating > integrated rating),* and 2 if the applicant integrated rating is adjusted upwards *(final rating < integrated rating).* All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 7. Negative binomial (NBR) and OLS regressions of *Time to Lending*

VARIABLES	(1) NBR	(2) NBR	(3) NBR	(4) NBR	(5) NBR	(6) OLS	(7) OLS	(8) OLS	(9) OLS	(10) OLS
Final rating	0.219**	0.290***	0.141*	0.219***	0.222***	0.277**	0.193**	0.116	0.125*	0.134*
	(0.106)	(0.092)	(0.085)	(0.079)	(0.074)	(0.107)	(0.092)	(0.088)	(0.073)	(0.075)
Final rating ^{2}	-0.008	-0.014***	-0.007	-0.013***	-0.012***	-0.011*	-0.008	-0.005	-0.007	-0.008
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
BHD	0.264**	0.266**				0.344**	0.180			
	(0.133)	(0.112)				(0.165)	(0.116)			
BHD x Final rating	-0.024*	-0.033***				-0.029**	-0.026**			
	(0.012)	(0.011)				(0.014)	(0.009)			
BHD_2			0.504***	0.353***	0.412***			0.540***	0.270***	0.259***
			(0.076)	(0.062)	(0.084)			(0.076)	(0.058)	(0.069)
BHD_2 x Final rating			-0.019**	-0.024***	-0.027***			-0.021**	-0.024***	-0.025***
			(0.008)	(0.007)	(0.008)			(0.008)	(0.008)	(0.008)
Observations	447	447	447	447	447	447	447	447	447	447
Controls	NO	YES	NO	YES	YES	NO	YES	NO	YES	YES
Area FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Branch Dummies	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
R2/Pseudo R2	0.0099	0.1096	0.0810	0.1181	0.132	0.067	0.529	0.385	0.544	0.574

Note: in columns (1)-(5) the dependent variable is *time to lending,* a continuous variable computed as the number of days necessary for the loan approver to reach the final lending decision on a given credit application, while in columns (6)-(10) the dependent variable *time to lending* is computed as the logarithm of 1 + the number of days necessary for the loan approver to reach the final lending decision on a given credit application. Columns (1)-(5) show the estimation results for the negative binomial regression model, while columns (6)-(10) show the estimation results for the ordinary least squares regression model. Columns (1), (3), (6) and (8) display the restricted version of the model, while Columns (2), (4), (5), (7), (9) and (10) display the unrestricted version of the model. Columns (5) and (10) include branch dummies. All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 8. Logit regressions of *Loan Distress*

VARIABLES	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
BHD	0.009	0.940	0.062	0.968	-0.010	1.079*
	(0.177)	(0.756)	(0.176)	(0.793)	(0.202)	(0.622)
Final rating	0.525***	0.987***	0.548***	0.982***	0.559***	1.114***
	(0.091)	(0.348)	(0.088)	(0.353)	(0.090)	(0.289)
BHD x final_rating		-0.089		-0.083		-0.107**
		(0.065)		(0.064)		(0.051)
Discretion up			-1.221**	-0.209		
			(0.616)	(1.464)		
BHD x Discretion up				-0.186		
				(0.302)		
Discretion down			0.500	0.819		
			(0.419)	(1.666)		
BHD x Discretion down				-0.058		
				(0.304)		
Uncodified up					-3.785**	-0.541
					(1.550)	(2.006)
BHD x Uncodified up						-0.630**
						(0.338)
Uncodified down					0.662	-4.414**
					(0.928)	(2.296)
BHD x Uncodified down						1.268**
						(0.599)
Codified up					-0.428	0.495
					(0.547)	(1.888)
BHD x Codified up						-0.272
						(0.329)
Codified down					0.407	2.012
					(0.482)	(1.410)
BHD x Codified down						-0.312
						(0.259)
Observations	447	447	447	447	433	433
Controls	YES	YES	YES	YES	YES	YES
Area FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
R2/Pseudo R2	0.311	0.320	0.341	0.350	0.369	0.401

Note: in columns (1)-(6) the dependent variable is *loan distress,* a binary variable equal to 1 if the loan becomes past due, unlike-to-pay, forborne or non-performing in the two years after the loan has been disbursed and 0 otherwise. Columns (1) and (2) show regressions performed according to model (4), while columns (3)-(6) report regressions performed according to model (5). All variables are defined in Table 2. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Appendix

I. Qualitative questionnaire (corporate)

Section A - Industry analysis and competitive position

A1 - Current industry cycle

a. recession b. expansion c. stability d. stagnation

A2 - Expected industry cycle

a. recession b. expansion c. stability d. stagnation

A3 - Market type

a. non-cyclical b. cyclical c. volatile

A4 - Market structure

a. low competitive b. highly competitive c. competitive

A5 - Competitive position

a. leader b. competitor

A6 - Investment requirements

a. low b. high c. medium

A7 - Market share and margins

a. below the average b. above the average c. average

A8 - Investment requirements

a. stable b. growing c. declining

A9 - Specific risk

a. none b. raw materials, energy, currency c. suppliers, distribution d. more than one

A10 - Specific risk exposure

a. null b. low-medium c. high d. very high

A11 - Operative leverage

a. below the average b. above the average c. average d. high

Section B - Corporate specific

B1 - Geographic diversification

a. local b. national c. multinational d. international

B2 - Client diversification

a. diversification b. concentration

B3 - Product diversification

a. low b. high c. medium

B4 - Past strategy – management track record

a. satisfactory b. successful

B5 - Future strategy

a. external growth b. internal growth c. debt reduction

B6 - Stock performance

a. low value b. high c. low growth d. high growth e. non listed

B7 - Financial flexibility

a. low b. medium c. high d. very high

B8 - Source of financing available

a. credit lines wide and diversified b. committed credit lines c. banks, bond, equity d. information not available

B9 - Existence of risk of legal cases pending and tax / social and welfare disputes

a. no b. yes, there are minor legal proceedings (value < 10% of partners equity) c. information not available

B10 - Environmental risks: the business exposes the company/group to environmental problems (use of harmful substance, pollution, workplace safety)

a. no b. yes, there but the company/group operates in compliance with regulations by adopting protective measures
c. information not available

B11 - Recourse to C.I.G. (redundancy fund) in the past 2 years

a. no b. yes

B12 - Judgment of the auditors and the statutory boards on the quality of the financial statements

a. judgement without exception b. judgement with exception

B13 - Criteria for the evaluation of financial statement items

a. prudential b. market-based

Section C - Group influence

C1 - Does the company belong to a group?

a. no b. yes c. yes, it belongs to a creditworthy group with low probability of counterpart's insolvency

II. Examples of override notes

A. ***Rating upgrades***

Excerpt from an override note of 02/14/2012.

The override proposal is based on the following reasons: excellent capital base; good and stable financial support from shareholders under the cooperative system; occasional increasing level of inventories due to a strong advance of the harvest for climatological reasons.

Excerpt from an override note of 05/17/2012.

The company is planning the sale of the "energy" branch - as evidenced by the mandate given to the XXX bank for the sale of ZZZ (the sub-holding of the energy branch) for a realizable value estimated by our M&A in 250/280 million euros - with a reduction of the consolidated net debt position of the group of 55/60 million euros. A further debt reduction of 145 million euros (debt repayment + capital gains) will come from the divestment program concerning not used properties (market value of 176 on a compendium of 296 million euros).

Excerpt from an override note of 05/30/2012.

The company's business, now fully operational, produces a cash flow more than sufficient to repay existing loans, to date all following the regular amortization schemes. The business plan presents economic data virtually certificates and the sharp reduction of structural costs realized over the past two years should allow already for the current year to achieve balance sheet profits. The upcoming capital increase will result in an improvement in the capital structure of the company.

Excerpt from an override note of 06/12/2012.

The submitted override proposal is based on the following considerations: first of all the positive trend of the first quarter with a turnover of USD 21million (EUR 16million) upper well 4.2million compared to the YTD budget. The EBTIDA (Earnings Before Interest, Taxes, Depreciation and Amortization) is reported to be positive for USD 6.3million, confirming the recovery in the freight market. The XXX contract will generate a margin of EUR 14million as reported in the notes and the LTV (Loan to Value overall) is lower than the industry average, as reported in detail fleet.

Excerpt from an override note of 08/13/2012.

Upgrade override to M4 (in line with previous year) requested in light of: (i) XXX's leading market position in Europe and attractive portfolio of production including VVV, YYY, WWW and ZZZ; (ii) profitability in 2011 was heavily impacted by impairments of euro 18.4mln (2010: euro 1.1mln) and discontinued operations in Romania and France of euro 29.9mln (2010: euro 20.9mln); (iii) solid free cash flow generation that is expected to compensate for the large Capex programme over the next three years; (iv) although leverage at the end of the year increased to 7.18 (2010: 2.95) as a result of the acquisition of ZZZ (partially financed by debt), the company is targeting leverage of below 3 by 2015.

B. *Rating downgrades*

Excerpt from an override note of 01/17/2012.

It is considered appropriate to place the company's rating at level M4 given the credit standing of its only assets represented by participations in XXX.

Excerpt from an override note of 02/08/2012.

The continuing crisis in the sector has resulted in additional cash requirements compared to the initial forecasts made at the beginning of the ambitious investment program. The need to cope with the increasing debt service has led recently the company to ask the lending banks for a temporary suspension of payments. The loan position of the company, already classified as problematic, recently was classified in RIO (Risk Under Scrutiny). Hence, we review the rating at High Risk.

Excerpt from an override note of 02/20/2012.

This is a marginal customer relationship from which we intend to exit.

Excerpt from an override note of 08/25/2012.

We proceed to make conservative override of position bringing the rating from R1 to R3 since the XXX is ranking to RIO (Risk Under Scrutiny).