Hardening Soft Information: How Far Has Technology Taken Us?*

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Abstract

In this paper, we explore the boundaries of soft information. Specifically, we investigate the extent to which soft information can be "hardened" in commercial loan underwriting such that it can be communicated unimpeded across the hierarchical layers of large banking organization. We use a proprietary dataset from a large European bank containing granular loan-level information on the credit score building process and its loan approval decisions. Like other banks, soft information is injected into the process at several points. We find that credit scoring technology does not eliminate the barriers to an unbiased and credible communication of soft information at distance within a banking organization. In addition, we find that firms applying to distantly located branches receive a lower amount of credit than firms with the same score applying to branches closer to the bank office with final approval authority. Our findings confirm the persistence of spatially-based organizational frictions even in the context of a modern credit-scoring based lending technology.

Keywords: *Credit scoring, communication problems, bank organization, loan officer discretion*

JEL codes: G21, L14, D82

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1. Introduction

The academic literature has suggested the possibility that technological innovation has "hardened" information used in loan underwriting and increased the ability of banks to lend to opaque borrowers at a greater distance (e.g., Petersen and Rajan 2002, Berger 2015, Udell 2015). In this paper, we empirically investigate the extent to which technology has succeeded in this regard and, by implication, the extent to which information technology may have fundamentally transformed the nature and organization of commercial loan underwriting.

Our empirical strategy is based on the idea that if soft information can be successfully hardened then the problems associated with transmitting this information through the hierarchical layers of large banking organizations (investigated inter alias by Stein (2002)) diminishes. The laboratory for our exploration is the corporate loan underwriting activity of a large European multinational bank. Using loan level data we can analyze the degree to which a large hierarchical bank hardens soft information through its commercial loan credit scoring model. More specifically, we examine the extent to which hardened soft information can be successfully transmitted unimpeded through the bank's hierarchy.

Commercial loan underwriting at large banks is typically extruded through the process of building a credit score on which the lending decision will ultimately be based. Much of the credit score will depend on *hard* information typically defined in the academic literature as objective, quantitative data that can be communicated at a distance without any material loss of content (e.g., borrower financial statements, balance-sheet ratios, repayment records, etc.). However, the credit scoring process can also involve the injection of soft information. That is, large banks may allow and/or require the originating loan officer to inject *soft* information about the borrower at one or more points in the process of building the credit score. The academic literature typically defines soft information as subjective knowledge accumulated over time by loan officers in the course of repeated face-to-face interactions with borrowers (e.g., subjective assessments of the quality of the firm's strategy, management, customer relationships, reputation, etc.). This injection of soft information generated by the loan officer into the credit score involves the transformation of this subjective information into a quantifiable input. It is in this sense that soft information is "hardened."

While the mechanics of "hardening" soft information and injecting it into a credit score is straightforward (see below), the actual use made by loan officers of their discretionary power of "hardening" subjective information and the value of this information in lending decisions is another matter. More specifically, the issue of whether soft information can be hardened successfully is unsettled in the academic literature. On the one hand, there is a considerable amount of theoretical and empirical literature on lending that emphasizes that soft information is not easily codifiable, storable or objectively verifiable and that it is very local in nature, largely embedded in local society and the economic environment. As a result, transmitting soft information generated by the loan officer through the banking organization at a distance can be highly problematic.[1] On the other hand, there a number of papers that suggest the possibility that innovation in information technology may have fundamentally moved the boundaries of soft information transmission (e.g., Petersen and Rajan 2002, Berger 2015, Udell 2015). More specifically, there is evidence that the adoption of credit scoring, in particular, has reduced the cost of collecting and processing information (Akhavein *et al.* 2005; Brevoort and Wolken 2009), and helped to standardize the language within the banking organization, facilitating the communication and transmission of information across bank hierarchical layers (Crémer et al. 2007, Bloom et al. 2009).

By way of background, credit scoring technologies usually rely on statistical inputs designed to appraise the creditworthiness of a loan applicant. The outcome is summarized in a numerical score/rating that typically reflects a firm's probability of defaulting over a given time span (usually one year). But, as we noted above, the credit score building process in practice can also involve soft (i.e., qualitative) information where loan officers inject subjective knowledge about the business and its prospects. Our goal is to analyze whether this works. That is, we seek to analyze the extent to which credit scoring allows loan officers to harden soft information such that it can be transmitted through the bank's hierarchy and successfully incorporated into the final credit score and the final loan decision. In that regard we seek the answers to two fundamental questions: (i) Is the use of soft information and the exercise of discretion by loan officers entrusted with completing the credit scoring process independent of the distance from the banks' headquarters where their activity and the activity of their branches are ultimately assessed? (ii) Does hardened soft information generated by the officer get fully incorporated into the final lending decision, or does the distance between the bank's office where the authority for loan approval resides and the branch producing affect the decision on whether and how much to lend?

[1] The terms functional and hierarchical distance are often used interchangeably in the literature to identify the distance between the branches and strategic/decisional centers of the bank (DeYoung et al. 2004; Alessandrini et al. 2009). In this paper, we will distinguish between the two according to the power and responsibilities of the bank's central offices and the type of decision analyzed (credit scoring versus lending decisions). Precisely, by *functional distance* we denote the distance between the branch where information on borrowers is collected and credit scoring is formulated and the bank's main headquarters where the ultimate assessment of branch and loan officer activities are made. In contrast, *hierarchical distance* is the distance between the branch producing the score and the office with the power of loan approval, which can be the branch itself (in this case the hierarchical distance is zero), the bank's main headquarters (in this case the hierarchical distance coincides with the functional distance) or an intermediate bank office. Transmitting soft information at a functional/hierarchical distance within a banking organization can be exacerbated by both physical and cultural factors. For example, the cost of effective loan review tends to be higher where physical distance between the bank's headquarters, where loan reviewers report (Berger and DeYoung 2001; Berger and Udell 2002). At the same time, physical and cultural distances reduce affinity between communicating parties (Cremer et al. 2007), undermining mutual trust and information reliability, and exacerbate banks' home bias (Giannetti and Laeven 2011; Presbitero et al. 2014), making the budgeting for faraway branches and career opportunities for loan officers located there stricter.

In our analysis we use a proprietary dataset containing very granular information on the credit scoring process and the final loan approval decision in a large sample of commercial loans. We distinguish between two moments in the credit scoring process in which the loan officer can use her discretionary personal judgment about borrower creditworthiness by hardening pieces of soft information. The former, that we label *codified discretion*, involves soft information related to the assessment of specific borrower characteristics that are predefined by the bank in a questionnaire that loan officers responsible for a credit scoring are required to complete and whose answers are codified and mapped into a numerical score. The second moment, labeled *uncodified discretion*, allows loan officers to deploy all soft information (subjective information that is not limited to specific characteristics) that is not codified and is not converted into a numerical score. Instead it is expressed as an override recommendation justified by specific, detailed notes, which are reviewed and approved by the bank's *Rating Unit* located at the main headquarters. Once the credit score is generated, information is transmitted to bank officers with the responsibility for the loan approval, which can be the same loan officer who compiled the score, another officer at the same branch or a manager at an intermediate or main bank headquarters.

On the whole, our results indicate that there are some limits to the hardening of soft information in credit scoring and that the adoption of this technology does not eliminate communication problems across bank hierarchical layers and the adverse effects of spatially-based organizational frictions in lending. First, we find that loan officers located in branches at a greater distance from the main bank headquarters to which loan reviewers report and where branch budgeting and loan officer careers are eventually determined (hereafter *functional distance*; see footnote 1) are more likely to inflate the *statistical rating* by submitting positive responses to the codified questions of the questionnaire. On the other hand, we find that higher functional distance is associated with a significant lower probability that loans officers use uncodifed discretion. These results are consistent with loan officers strategically "gaming" for bonuses and career advancement by inflating the applicant scores in the codified step where they are not subject to adjustment by the loan authority and are less exposed to external inspection and reputation risks (Berg et al. 2013; Brown et al. 2013; Mosk 2014). In contrast, loan officers in remote branches appear to be cautious in transmitting soft information by submitting override proposals and detailed personal notes on borrowers, which are subject to review and approval at the headquarters. Finally, we find that, the final rating being equal, the amount of credit accorded by the bank manager with loan approval authority significantly decreases with the distance from (the branch of) the loan officer originating the score (*hierarchical distance*).

The rest of the paper is organized as follows. Section 2 reviews the related literature on credit scoring, loan officer discretion and lending decisions. 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 empirical results related to the use of discretion and injection of soft information in credit scoring, while Section 6 discusses results on the lending decisions. Section 7 concludes.

2. Related literature

Our research is primarily related to three strands of the literature. First, and most closely related, is the recent literature on loan officer discretion, information production and manipulation in credit-scored lending. Second, is the literature on credit scoring and information communication costs. Finally, our paper is related to the literature on communicating and lending at a functional distance.

2.1. *Loan officer discretion and information manipulation in credit-scored lending*

A number of recent studies have focused on information manipulation in credit scoring and on factors driving loan officer discretion in information production and lending decisions. Brown et al. (2012) examine the credit scoring process of nine Swiss banks and show that in the presence of positive and negative shocks that would change a borrower's quantitative (hard-information based) score, loan officers make significant use of their discretionary power by adjusting their qualitative assessment and overriding the system's score to smooth the impact of the shocks on credit ratings. To the extent that rating adjustments are largely unrelated to future loan performance and are more likely at banks which explicitly use rating classes to fix interest rates, loan officers seem to exercise discretion to smooth the effects on interest rates for their clients rather than to incorporate private information. Berg et al. (2013) and Mosk (2014), using data from a single European bank, find that loan officers manipulate internal ratings through multiple scoring trials in order to increase the probability of a loan approval. Consistent with the theoretical predictions in Dessein (2002), information manipulation by loan officers responsible for the screening process tends to be strategically high when the loan approval authority is delegated to high-ranking managers (see also Bouwnes and Kroos 2012). In a similar vein Campbell (2012) finds that loan officers of a large credit-union in the US that were hired after the organization underwent a strong decentralization of the lending process are more likely to approve problematic loans for which internal guidelines on credit scores and debt-to-income ratios would point to a credit denial.

More related to our research focus on functional distance and loan officers discretion, Scott (2004) analyzes a large sample of US small and medium enterprises, finding that soft information production is significantly higher for firms borrowing from small community banks and when loan officers responsible for the relationships do not rotate over time. Similarly, Uchida et al. (2012) document that loan officers at branches of small (functionally closer) regional banks in Japan tend to produce more soft information than loan officers at large (functionally distant) banks, while Ogura and Uchida (2014) show that banks experiencing a consolidation or an increment in their organizational complexity rely significantly less on soft information production.

Using an approach to measure the discretionary use of soft information by loan officers similar to ours, Gropp et al. (2012) show that loan officers at small saving banks in Germany are more likely to upgrade the financial (hard-information-based) rating of applicants than their colleagues at large saving banks, while the downgrades of financial ratings are not significantly different between the two groups of banks. Our paper differs from Gropp et al. (2012) in three main ways. First, having detailed information from loan application folders, we are able to identify the location of our loan officers. Thus, we can measure the impact of the within-bank functional distance on the likelihood that the loan officer who compiles the credit score will exercise discretion in adjusting financial scores. Second, we distinguish between two moments in which loan officers can inject their subjective information into the credit scoring process, 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. Third, we also investigate whether communication frictions within the banking organization affect the degree of reliability that bank managers responsible for loan approval attribute to soft information injected into the final credit score by loan officers. In particular, we test whether the hierarchical distance between the bank's office with the approval authority and the local loan officer generating the credit score has an adverse impact on the lending decisions independent of the applicant's final rating.

Brown et al. (2013) consider the use of discretion by loan officers of six Swiss banks during the process of credit scoring. 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 upward or downward override of the applicant's rating based on a detailed report about the reasons for the proposed override. They document that when the scoring has to be approved by a credit manager, loan officers tend to increase the qualitative assessment of applicants more than the likelihood of overriding, and that this is especially true when the approver manager has already downgraded some of their past proposals. These findings indicate the existence of communication problems within banking organizations that would induce loan officers to strategically prefer injecting codifiable rather than uncodifiable soft information into the rating given oversight by higher ranked managers with whom they have interacted with in the past.

Agarwal and Hauswald (2010) analyze lending decisions by a large US bank on new loan applications presented by small- and medium-sized enterprises. Consistent with the idea that credit scoring reduces information bias in communicating at a functional distance, they find that the likelihood of delegating lending authority to loan officers by requesting further information and a credit recommendation increases with the branch-to-headquarter distance. In addition, they find that loan officers at branches further away from the bank's headquarters are more likely to provide detailed written notes to justify their credit recommendations, if they have real authority in the lending process. This is in contrast to Gropp et al. (2012) and to our results on the negative impact of functional distance on the production of uncodifiable soft information. However, it is in line with our results on the positive association between functional distance and codified discretion.

Puri et al. (2011) using data from consumer loans at German saving banks find that the loan officers responsible for the loan origination are more likely to override a latent rejection decision based on the automatic internal scoring if the applicants are old customers, having longer and wider relationships with their bank. The ex post performance of such discretionary loans is not different from otherwise comparable loans whose internal score is above the cutoff of automatic approval, suggesting that loan officer discretion helps to improve the selection of applicants.

Finally, Degryse et al. (2014), using a detailed data set from a small business lending division at an Argentinian bank, show that loan officers exercise discretion by exceeding the credit limit established on the basis of the internal credit score if they possess favorable soft information about the applicant. Once again, differently from this paper we directly investigate the existence of communication frictions within the bank organization due to the distance between hierarchical levels and distinguish between types of soft information on the basis of the mode (codified questionnaire versus uncodified written notes) of transmission of subjective knowledge generated by local loan officers.

2.2. *Credit scoring and communication frictions*

A number of studies have found evidence that credit scoring can mitigate organizational frictions due to distance. Indirect evidence, for example, is provided by Akhavein et al. (2005) and Frame et al. (2004) who find, respectively, that the large US banking organizations that first adopted small business credit scoring techniques in the '90s were those with a large number of geographically dispersed branches, and that the adoption of credit scoring increased the amount of small business lending in markets far from the banks' headquarters. Similarly for Italy, Albareto et al. (2011) find that large banks were the first to make use of credit scoring models in their lending decisions. In addition, Mocetti et al. (2010) and Del Prete et al. (2014) document that banks using credit scoring technologies have a more decentralized organization.

More directly, DeYoung *et al.* (2008) and Paravisini and Schoar (2013) provide evidence that the introduction of credit scoring techniques in loan underwriting improves information processing and reduces asymmetries of information within a bank organization by making internal communication more reliable. DeYoung et al. (2008, p. 134) show that the adverse effect of borrower-lender distance on the borrowers' probability of default is "largely neutralized at banks that used credit scoring techniques", regardless of whether these credit scoring techniques are fully automated or allow for discretionary loan officer use of soft information. Paravisini and Schoar (2013), using data from a trial experiment considering the introduction of a new credit scoring model at a Colombian bank, find that in branches that were randomly included in the pilot program the loan underwriting process significantly improved in terms of the time credit committees devoted to the evaluation of a loan application and probability of credit committees making a decision increased. They also find that it is the existence of scoring itself (i.e., just knowing that a score will become accessible) more than the actual score to increase the reliability of information produced by the loan officer in charge of the application, suggesting that the benefit of the adoption of a credit scoring technology comes from the reduction of information asymmetry between the loan officer and credit committee (the agency channel) more than from the lower costs of information acquisition (the information channel). These papers, however, do not distinguish between types of soft information (codifiable versus uncodifiable). In addition, they do not consider the impact of credit scoring on information transmission within the bank organization and how this is influenced by the distance between the originating loan officers (who produce information) and those who are responsible for the loan approval.

More broadly Berger (2015) offers a literature review on the subject of "hardening" information that points out that the evidence on small business lending suggests a "greater use of hard information or a 'hardening' of the information used." Berger (2015) also emphasizes the role of technology in explaining the increased use of hard and "hardened" information. But, at the same time this literature review expressed skepticism about technology's effect on the role soft information noting that "it seems unlikely that technological change has had as much effect in improving soft information technologies … [where] qualitative data are less subject to improvements in the processing and transmission." This highlights the key issue that we address in this paper. Is the "hardening" of information that is observed in the academic literature limited to a shift in emphasis from soft information to hard information – or is does "hardening" include the transformation of soft information into hard information? And, if so, what type? In another recent overview paper, Udell (2015) argues that this one of the key unsettled issues in lending: can "technological innovation [can] covert some soft information into hard information that can be transmitted within a large complex bank?" This is precisely the issue we address in this paper.

2.3. *Communicating and lending at a functional distance*

The literature on functional distance in banking has analyzed various issues, including access to credit

(Mian 2006; Detragiache *et al.* 2008; Alessandrini *et al.* 2009), loan terms (Jimenez et al. 2008; Gambacorta and Mistrulli 2014), relationship lending (Presbitero and Zazzaro 2011), and bank efficiency (Berger and DeYoung 2001). On the whole, studies conducted at the market, bank and loan level show that branches and subsidiaries of functionally distant banks inhibit from small business lending and soft-information-based credit relationships (Mian 2006; Detragiache *et al.* 2008; DeYoung *et al.* 2008; Benvenuti *et al.* 2013; Cotugno *et al.* 2013). Consistently, firms located in regions disproportionally populated by functionally distant banks have less access to credit, a lower capacity to maintain a long-lasting bank relationship and a lower propensity to innovate (Detragiache *et al.* 2008; Alessandrini *et al.* 2009, 2010; Gormley 2010; Presbitero and Zazzaro 2011). Evidence of the constraining impact of functional distance on lending has also been found in the recent global financial crisis in which a "flight to home" effect has been linked to the decline in lending in regions farther away from bank headquarters (Giannetti and Laeven 2011; De Haas and Van Horen 2013) and the restriction in access to credit to firms located in regions populated by foreign and functionally distant banks (Popov and Udell 2012; Presbitero *et al.* 2014).

More relevant for our study, Liberti and Mian (2009) analyze loans to large corporate customers made by a large 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. In a similar vein, Qian *et al.* (2015) study the relation between communications costs and information production in a large Chinese bank, confirming the importance of a "human touch" and socio-cultural proximity in communication. Namely, they find that internal ratings have more power to predict default when the time since the loan officer and the branch president work together is longer and they had the opportunity to know and trust each other thoroughly. These studies, however, do not consider the impact of functional distance on the discretionary use and transmission of soft information by local loan officers. In addition, they typically focus on small business lending, while we test whether the impact of functional distance keeps its significance in credit-score lending to medium-large enterprises.

3. The bank lending environment: Details on the credit score building process

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

3.1. *Credit scoring process*

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 scoring process at our bank.

[Figure 1]

The credit scoring process is initiated by a loan officer at the local branch to which the company applies. Loan officers are assigned to applications randomly, according to a queueing system. 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 the firm's quantitative financial statements. 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 integrate 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 management quality, ownership and organizational structure. While this subjective assessment is quantified into a numerical score, 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 score given by the loan officer on each specific question enters 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 reported 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*. 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 soft information used at this stage is standardizable and codifiable on a numerical scale by the loan officer, and because of the mandatory nature of the qualitative questionnaire which does not involve proactive behavior on the part of the loan officer nor 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, the loan officer has to provide a written motivation to the upper layer of the bank. Rating deviations may encompass one or more than one rating notch giving rise to 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 and expanding demand, or participation in projects with strong creditworthy partners. Proposed rating upgrades need to be approved by the specialized *Rating Unit* located at the bank's headquarters.[2] In contrast, downgrades are approved automatically by the system, even if written notes produced by the loan officer are also exposed to potential inspections by the loan reviewers at the headquarters with possible reputational ramifications that could affect his/her career prospects.[3]

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.

3.2. *Lending process*

[2] From credit files we can observe approved rating overrides, while we cannot gain any information on override proposals.
[3] Although our bank does not follow a "formal" incentive payment scheme, the compensation of loan officers typically includes, besides a fixed salary, extra bonuses based on their individual performance in terms of loan quantity and on the overall performance of the branch where they work, which are distributed each year at the discretion of the bank..

From the moment that the loan officer originates a credit score, he/she cannot modify his/her appraisal anymore. Then, the loan application and the credit scoring generated by local loan officers goes through the bank's hierarchy to the manager(s) with the authority to make the final decision on loan approval and the credit amount. The hierarchical design of our bank involves eleven levels of approval*,* with the loan officer originating the credit score at the lowest level and the executive board at the highest (see figure 2). In the first nine hierarchical levels of approval a single bank manager has the authority to make a final decision on the loan application, whereas in the last two hierarchical levels the designated loan approving authority is a committee. The geographical location of the loan decision-maker varies with the level of approval. At the second hierarchical level the loan officer examining the loan application and submitting the credit score and the ultimate decision-maker work in the same branch, thus minimizing problems of information transmission and favoring 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 place 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.

[Figure 2]

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.

Table 1 reports the distribution of applicants in our sample according to the hierarchical level of approval and the hierarchical distance from the ultimate bank officer approving a 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.

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 (CIB) 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 functional 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. *Loan officer discretion*

The first issue we investigate is whether and how communication frictions related to functional distance affect the use of discretion by loan officers in the credit scoring process.

4.2.1. *Estimated models and dependent variables*

The empirical model for loan officer discretion is:

$$\textbf{(1)} \quad Discretion_i = f[\beta_0 + \beta_1(Functional\ distance)_i + \sum_j \beta_{2,j}(Loan\ officer\ characteristics)_{ji} + \\ + \sum_h \beta_{3,h}(Loan\ characteristics)_{hi} + \sum_k \beta_{4,k}(Firm\ characteristics)_{ki} + \varepsilon_i]$$

where the subscript *i* indicates the loan officer.

We use three measures of discretion: (i) *Total Discretion*, that is the difference between the *final rating* and the *modified statistical rating*; (ii) *Codified Discretion*, that is the difference between the *integrated rating* and the *modified statistical rating*; (ii) *Uncodified Discretion*, that is the difference between the *final rating* and the *integrated rating*. First we estimate a logit model to test for the determinants of the likelihood that loan officers use subjective discretion in the credit scoring process.[4] In this case, the three *Discretion* variables are dummies assuming values of 1 if measures (i)-(iii) are different from 0, that is if loan officers exercise discretion by adjusting, downwards or upwards, the applicant's statistical score.

If $\widehat{\beta_1}$ 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 problems in communicating and transferring codifiable and/or uncodifiable soft information to the upper hierarchical layers of the bank. In contrast, a statistically significant coefficient for *Functional distance* indicates the existence of communication problems

[4] We also use a probit model obtaining practically the same results (available upon request).

within the banking organization that influences systematically the use of soft information by loan officers at distant branches. If $\widehat{\beta_1} < 0$, 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 lenders and loan reviewers that are culturally and physically very distant. On the contrary, $\widehat{\beta_1} > 0$ indicates that loan officers at distant branches are more likely to use their subjective knowledge to adjust the automated statistical score, possibly to increase the probability of loan approval and generate an extra performance bonus (see footnote 3). Finally, a negative coefficient for *Functional distance* in the *Uncodified Discretion* model and a positive coefficient 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 - written notes.

We also analyze the probability that loan officers exercise their discretion to improve or worsen the credit rating of the applicant. In this regard we estimate a multinomial logit model in which T*otal Discretion_012*, *Codified Discretion_012* and *Uncodified Discretion_012* 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. Specifically, we estimate:

$$Total\ Discretion = \begin{cases} 2 & \text{if } \textit{Final Rating} < \textit{Modified Statistical Rating} \text{ (upgrade)} \\ 1 & \text{if } \textit{Final Rating} > \textit{Modified Statistical Rating} \text{ (downgrade)} \\ 0 & \text{if } \textit{Final Rating} = \textit{Modified Statistical Rating} \end{cases}$$

$$Codified\ Discretion = \begin{cases} 2 & \text{if } \textit{Integrated Rating} < \textit{Modified Statistical Rating} \text{ (upgrade)} \\ 1 & \text{if } \textit{Integrated Rating} > \textit{Modified Statistical Rating} \text{ (downgrade)} \\ 0 & \text{if } \textit{Integrated Rating} = \textit{Modified Statistical Rating} \end{cases}$$

$$Uncodified\ Discretion = \begin{cases} 2 & \text{if } \textit{Final Rating} < \textit{Integrated Rating} \text{ (upgrade)} \\ 1 & \text{if } \textit{Final Rating} > \textit{Integrated Rating} \text{ (downgrade)} \\ 0 & \text{if } \textit{Final Rating} = \textit{Integrated Rating} \end{cases}$$

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, $\text{Prob}(Discretion\_012 = z) = \text{Prob}(x_{iz}'\beta + \varepsilon_{jz} > x_{iz'}'\beta + \varepsilon_{iz'})$ 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 2003):

$$\text{(2)} \qquad \text{Prob}(Discretion\_012 = z) = \frac{\exp(x_{iz}'\beta)}{\exp(x_{i0}'\beta)+\exp(x_{i1}'\beta)+\exp(x_{i2}'\beta)}$$

As equation (2) makes clear, the independence of ε_{iz} implies that the odds ratio $\text{Prob}(Discretion\_012 = z)/\text{Prob}(Discretion\_012 = z')$ to be independent of the excluded alternative. For the type of decision 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 dependent and explanatory variables used in the analysis and some descriptive statistics. In 44% of the loan applications loan officers changed the modified statistical rating based on pure hard information. In 36% of 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 *uncodifiable discretion.* This is augmented with detailed explanatory notes to senior managers. In 69% of these cases by recommending an upgrade, and in 31% by recommending a downgrade.

4.2.2. *Explanatory variables*

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

Our key explanatory variable is *Functional distance*. Following Alessandrini *et al.* (2009), *Functional distance* is measured by 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. Defining *functional distance* in this manner is specifically appropriate in our setting because the *Rating Unit* responsible for the approval of score overrides is located, in fact, at the bank's headquarters, and this is the hierarchical level where loan officer performance (including credit score origination) and career trajectory are ultimately reviewed and determined.[6] *Functional distance* directly reflects communication frictions due to the spatial separation and lack of personal contact between bank officers that may inhibit the flow of soft information within the banking organization. However, *Functional distance* also captures cultural factors hampering information transmission and agency problems within the bank's hierarchy, such the lower cultural affinity between officers at the local and head branches, differences in languages, and lower mutual trust.[7] To the extent that our bank follows a uniform lending process and loan approval rules across branches, we can reasonably assume that the major (or the only) source of exogenous differences in the conduct of the bank headquarters toward branches is the variation in *Functional distance*. In our sample, the average branch-to-headquarter distance is 290.2 kilometers, with distance varying between 2.5 and 1,482 kilometers.

In order to isolate the effect of functional distance on the credit scoring process we control for a large number of possible confounding factors concerning the personal traits of the loan officers originating the credit score and characteristics of the applicant firms and lending relationships. Obviously, our cross-applicants analysis could suffer from selection and omitted variables problems. 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, and thus the functional distance between the branch and the bank headquarters, could be related to unobserved firm risk factors. The inclusion of a large number of firm control variables like firm size, collateral, capitalization, total debt and asset intangibility mitigates (even if does not eliminate) this concern, allowing us to interpret our results as capturing the fundamental relationship between communication frictions within a banking organization and the discretionary injection of soft information in credit scoring on the part of loan officers.

With regard to the loan officer characteristics, we first distinguish between males and females with the indicator variable *Gender* taking value 1 if the loan officer is male. Our sample contains individual data on 122 different loan officers belonging to 24 branches, 78% of which are males. Psychological, sociological and economic studies indicate that women are usually more risk averse and less overconfident than men

[6] Functional distance, as well as hierarchical and borrower-to-branch distances, have been measured through the online geospatial application Google Maps calculating the shortest distance from one location to another.

[7] Alessandrini *et al.* (2009, 2010) have also used a measure of *Functional distance* that is defined in terms of the difference in social capital between the provinces where the bank's branch and headquarters are located, documenting a strong correlation with the physical distance.

(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 (Loprest 1992; Fuller 2008; Del Bono and Vuri 2011). Women tend to be less selfish and competitive (Buser et al. 2014) and more selfless and supportive than men (Eckel and Grossman 1998, 2001; Dufwenberg and Muren 2006). These differences were found to influence loan officer behavior in loan origination, risk taking and lending relationships (Bellucci et al. 2010, Agarwal and Ben-David 2013; Beck et al. 2013).[8] In our context, greater risk-aversion, lower self-confidence and career concerns may discourage female loan officers from using soft information and exercising discretion, especially uncodified discretion. In contrast, 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 (2013) 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.

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. First of all, 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 that assumes the value 1 if the borrower buys at least one additional product 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 2000; Degryse and Ongena 2005; Agarwal and Hauswald 2010; Bellucci et. al. 2013). Fourth, we control for the delegation of authority within the banking organization in terms of the hierarchical level of loan approval (*Approval level*): to the

[8] 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).

extent that communication frictions increase with the hierarchical level to which loan officers communicate and given that loan officers know the hierarchical level with approval authority (i.e., the level to which they transmit their credit scores), the discretionary use of soft information can be affected by this factor. We use *Approval level* rather than *Hierarchical distance* to mitigate multicollinearity concerns with *Functional distance* and to have the most precise measure of delegation of loan approval powers.[9] 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 conflict of interests and 0 otherwise.[10]

Then we control for a set of borrower characteristics reflecting the firm's financial health and information transparency. First, we consider the applicant's rating that the loan officer must either confirm or adjust by including the variables *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 dummies to control for unobserved characteristics of local credit market and credit demand. We do not include branch dummies because they largely reflect the effects of distance from the bank headquarters (which is already controlled for). However, standard errors are clustered at the branch level to allow for heteroskedasticity and possible correlation of the error term within each branch due to some branch specificity.

4.3. *Lending decisions and functional distance*

Besides inhibiting the effective and unbiased hardening of soft information in the process of credit score building, frictions in communication across bank hierarchical layers could also affect the perceived reliability of the produced scores and then the final lending decisions. As a second step, therefore, we explore whether, the *final rating* being equal, decisions on the loan approval and the amount approved are influenced by the difficulty of passing on information within the banking organization, or what it is same,

[9] Correlation between *Functional distance* and *Hierarchical distance* is 0.41. In contrast, *Approval level* is only marginally correlated with *Funtional distance* (0.14). Anyhow, for robustness, in unreported regressions we control for *Hierarchichal distance* instead of *Approval level* or include both variables, obtaining results practically identical to those displayed in tables 3-6.

[10] According to banking 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. Hence, *Related lending* refers to situations of 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, reflecting a potential conflict of interest.

which is the value of "hardening" soft information in lending. In this case our key variable is *Hierarchical distance*. This is the distance between the loan officer originating the credit score and the manager(s) to whom the final loan approval decision is delegated. It captures communication problems between the subjects who are called to produce and use the soft information in the process of loan underwriting and allows us to test for the value and reliability of soft information hardened in the credit score.

4.3.1. *Estimated models and dependent variables*

The estimated empirical models for lending decisions are:

(3) $Approved_i \ = f[\alpha_0 + \alpha_1(Hierarchical\ Distance)_i + \alpha_2(Final\ Rating)_i + \sum_j \alpha_{3,j}(Controls)_{ji} + \varepsilon_i]$

(4) $Loan\ Amount_i \ = \beta_0 + \beta_1(Hierarchical\ Distance)_i + \beta_2(Final\ Rating)_i \ + \sum_j \beta_{3,j}(Controls)_{ji} + \eta_i$

where *Approved* is an indicator variable assuming values of 1 and 0 for approved and non-approved loans, respectively, and *Loan Amount* is the log of the approved credit amount. On average, 87% of loan applications are approved. The average size of approved loans is € 8,644,876.

First, models (3) and (4) are estimated separately. Then, since the sample of approved loans might not be randomly drawn from the population of applicants, we estimate a two-step Heckman model to correct for possible sample selection bias. Once again, a value of $\widehat{\beta_1}$ that is negative and statistically significant suggests that credit scoring does not eliminate communication problems related to hierarchical distance in the banking organization, as access to credit by firms having the same risk of default depends on the distance between the branch to which the firm applies and the office where the decision on loan approval resides.

4.3.2. *Explanatory variables*

Hierarchical distance is measured as the logarithm of 1 plus the kilometric distance between the branch where the loan officer who conducts the credit scoring process operates and the branch with loan-approval authority. The average *Hierarchical distance* of loans in our sample is 150.6 kilometers, with a minimum of 0 (when the loan approving authority is delegated to the loan officer herself, or the decision is made by a bank officer at the same branch) and a maximum of 1,576 kilometers.

To test whether credit scoring resolves communication problems within the banking organization we need to control for the rating attributed to the borrower. We use *Final rating* which is inclusive of any override decisions and incorporates all of the hard and soft information about borrower creditworthiness available to loan officers at the local level and transmitted to the approving authority.

Besides communication problems, *Hierarchical distance* could reflect the mechanical effect of the bank's rules for delegation of loan approval authority which require that larger loans and the loans of larger corporate borrowers must be approved at higher hierarchical levels. Then, in order to wash out the effect of the approval authority delegation rules within the bank and isolate the impact of information transmission problems on the likelihood of loan approval and the amount of credit, all regressions control for the hierarchical level at which the loan is approved (*Approval level*).

Additional controls include loan officer, borrower and loan characteristics described above for the discretion model (1). We also control for possible loan demand effects by including the variable *Overdrawn*, measured as the ratio of the loan amount used over total amount of loan granted (i.e., the total facility). Finally, we include geographical area and branch dummies[11] to control for unobserved characteristics. Standard errors are clustered at the branch level.

5. Exercising discretion in credit scoring

5.1. *Total discretion*

In Table 3 we report the results for the *Total discretion* model. Column 1 displays results of a logistic regression for the probability of observing a final rating different from the automated (hard information-based), modified statistical rating, while columns 2 and 3 display results of a multinomial logit for the probability of final rating being higher (downgrade) and lower (upgrade) of the modified statistical rating, respectively.

In both models, the coefficients on *Functional distance* are not statistically different from zero: distance from the bank headquarters does not affect he probability of loan officers exercising discretion by adjusting the statistical rating automatically produced by the credit scoring system. This result is arguably consistent with the hypothesis that credit scoring technologies make communication frictions between bank local officers and senior managers 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 *Total discretion*: a thirty eight year old loan officer (corresponding to the 10th percentile of *Age* distribution) is 21% more likely to exercise discretion

[11] In this case, the location of the hierarchical level of approval varies loan by loan and thus branch dummies are not strictly correlated with *Hierarchical distance*.

than a fifty six year old loan officer (at the 90th percentile (58% versus 37%).[12] If we compare loans approved by the loan officer him/herself (*Approval level* = 1) with those approved at the bank 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), 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. However, it is interesting to note that when we distinguish between upward and downward adjustments of the final rating we find that *Age* has a significant impact only on the probability of loan officers increasing the applicant's statistical rating (19% for a thirty-year old loan officer against 7% for fifty-six year old one), consistent with young officers inflating the credit score to increase the probability of loan approval. In contrast, the coefficient on *Approval level* is significantly different from zero only for the decision of loan officers to worsen the final rating, which is 25% more likely to be taken at the headquarters level than at the branch level (42% versus 17%). This suggests that when approval authority resides at the headquarters level, loan officers take a more cautious attitude when they evaluate loan applications, incorporating negative soft information into the approval decision, but not positive information.

Consistent with the finding on loan officer discretion in Brown et al. (2012), we find that risky applicants whose modified statistical rating is high are more likely to experience a reduction (increase) in their score. Specifically, the applicants classified as the most risky by the scoring algorithm solely on the basis of hard information (*Modified statistical rating* = 15) are 43% more likely to have their rating adjusted upwards (lower score) than the median risky applicant whose *Modified statistical rating* is equal to 8 (55% versus 12%), while the latter is 17% less likely to have a rating downgrade than the safest applicant whose *Modified statistical rating* is equal to 1 (23% versus 40%). Similarly, applicants having wider relationships with the bank (*Scope of relationship* = 1) are less likely to experience a downgrade in line with the hypothesis that the value of a lending relationship for the bank depends on the other non-credit services it cross-sells to its borrowers (Santikian 2013). Opposite effects on the probability of discretionary downgrading and upgrading of statistical rating are found for the size of applicant, with large firms being more likely to be upgraded and less likely to be downgraded by the loan officer examining their loan applications, once again suggesting a cross-selling effect. Finally, as expected, collateralized loans are more likely to be upgraded, while for loans with a potential conflict of interest, the probability of loan officer upgrade recommendation in the final rating is practically zero.

[12] 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.

5.2. *Codified and uncodified discretion*

In table 4 we split *Total Discretion* into *Codified Discretion* and *Uncodified Discretion*. In the former, the loan officer may adjust the modified statistical rating, which is produced automatically by the scoring algorithm solely on the basis of hard information, by incorporating his/her subjective (soft) knowledge of the applicant into codified responses to questionnaire questions. In the latter, the loan officer may propose a final adjustment of the applicant's score by communicating (arguably pure), non-codifiable soft information in the form of written notes attached to his/her application review.

5.2.1. *Functional distance*

Turning first to our key explanatory variable, it is interesting to note that the apparent insignificant impact of *Functional distance* on the exercise of loan officer discretion in the *Total discretion* model, in fact hides the separate (and opposite) effects for the two types of soft information input, *Codified discretion* and *Uncodified discretion*. In figure 3 we show the relation between *Functional distance* and the probability that a loan officer exercises each of the two types of discretion by *Functional distance* percentiles. Moving from the 10th to the 90th percentile of the *Functional distance* distribution the probability of loan officers deploying *Codified discretion* increases by 26%, from 21.5% to 47.6% (for loan officers at the median distant branch the probability of exercising *Codified discretion* is 35.5%). In contrast, the probability of loan officers overriding the *integrated rating* by communicating their subjective knowledge submitting specific notes on the applicant decreases from 24.2% to 4.9% (for loan officers at the median distance from the bank headquarter the probability of *Uncodified discretion* is 10%).

Also the direction in which codified and uncodified discretion are exercised and the score adjustment are not equally affected by *Functional distance* (figure 4). Loan officers at functionally 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 functionally close loan officers (specifically, 17% for loan officers at the 90th percentile of the *Functional distance* distribution and 1.5% for those at the 10th percentile), while the probability of downgrading is statistically unaffected by the distance from the bank's headquarters. In contrast, *Functional distance* has a sizeable decreasing impact on the likelihood of downward and upward overrides[13], such that for a loan officer at the 90th percentile of the *Functional distance* distribution the choice of not overriding is almost certain (96.5%).

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[13] It is interesting to note the effect of *Functional distance* 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 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*.

On the whole, this evidence suggests that credit scoring technologies cannot fully mitigate the communication frictions within the banking organization and that the "hardening" of soft information accessible to loan officers is influenced by how distant from the bank headquarters they are. 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. As a result, they are less likely to transmit pure, uncodifiable soft information to higher levels in the bank hierarchy relative to loan officers in branches close to the bank's headquarters. At the same time, consistent with the hypothesis of loan officers "gaming" the system for higher bonuses and career advancement, we find that functionally distant loan officers have 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 questions included in a mandatory questionnaire (Berg et al. 2013; Brown et al. 2013; Mosk 2014).

5.2.2. *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*) and loan officer gender seem to have effect only on the decision to exercise *Uncodified discretion*: specifically, *Experience* increases the likelihood of overriding the applicant's *integrated rating* (in particular, the probability of downgrading the *integrated rating*) and, consistent with the hypothesis of women's greater social-orientation, female loan officers are 7% more likely to adjust the applicant's score on the basis of their subjective, non-codifiable soft information relative to their male colleagues (12% and 5%, respectively).

The type of lending relationship (*Scope of relationship* and *Repeated lending*) does not have any significant impact 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 increasing the statistical rating of the applicant 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 asset distribution, the probability to exercise *Codified Discretion* upwards goes from 2% to 27%, while it goes from 33% to 17% for downwards adjustments. However, the size of the applicant has no significant influence on the decision to exercise *Uncodified Discretion*. Once again, this finding confirms the gaming hypothesis as loan officers tend to adjust upwards the score of large customers by inflating answers to the questionnaire, which will be unlikely corrected at the approval stage.

Finally, an interesting difference between *Codified Discretion* and *Uncodified Discretion* is that only the former seems to have an insurance content, as loan officers are more (less) likely to adjust upwards (downwards) the rating of risky applicants having a high modified statistical rating. By contrast, the worse (i.e., the higher) the integrated rating coming from the scoring algorithm the higher the probability that loan officers exercise *Uncodified discretion* to override the applicants' ratings upwards.

5.3. *Extensions and robustness*

5.3.1. *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 of Bouwnes and Kroos (2012) and (2012) 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 *Functional distance*.

The results are reported in table 5. 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 their *Codified Discretion* when they are responsible for loan approval. In contrast, loan officers that are functionally distant from the bank's headquarters are less likely to exercise their *Codified Discretion* if they have the power to approve the loan. In particular, as shown in figure 5, for loan officers located at the 10th percentile of *Functional distance* the probability of adjusting the automated statistical rating of applicants is 15% if the decision on the loan approval rests with other bank managers and 32% if they have the power to approve the loan. For loan officers located at the 90th percentile of the *Functional distance* the two probabilities are instead 57% and 29%, 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 *Functional distance* (the interaction term) is greater both in magnitude and statistical significance on the decision to upgrade the applicant's statistical score.[14] Once again, these results are consistent with the hypothesis that loan officers strategically make discretionary adjustments to credit scores in order to increase the probability of loan approval. That is, loan officers appear to game the system in response to incentives that encourage them to inflate ratings – and, moreover, these incentives arise because of problems related to the transmission of information at a distance.

5.3.2. *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 the number of observations decreases considerably, the results are robust to the inclusion of these additional controls. On the whole, they have a statistical significant influence only on *Uncodified Discretion*. Somewhat unsurprisingly *Long-term debt* and *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 *Functional distance* keep their sign and increase their 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.

6. Loan approval

The bank managers or credit committees having the formal authority of loan approval typically differ from loan officers who have produced the credit score and are often located at a distance from them. In this section we analyze whether communication problems within the banking organization due to the distance

[14] 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 *Functional distance* distribution (16% versus 18%) and at the 75th percentile the difference is almost 10% (14.3% versus 23.8%). For the probability to exercise discretion upwards, loan officers at the 25th percentile of *Functional distance* are 36% more likely to inflate the automated modified statistical rating if they have the approval power (4.9% versus 3.3%); by contrast, loan officers at the 75th percentile of *Functional distance* with loan approval delegation have 5.8% probability of inflating the applicant's score against 10% of loan officers without approval power.

between the local loan officer and the approval authority have a direct influence on lending decisions, beyond the indirect influence they exert through the formation of credit scoring.

In table 7 we report results of probit models for the decision to approve or reject the loan application (i.e., the extensive margin) and OLS regressions for the amount of credit granted (i.e., the intensive margin).[15] In order to maximize the number of observations in the basic specification (columns (1) and (4)), we control only for the applicants' *Final rating* to take into account the riskiness of applicants, and the hierarchical level of approval (*Approval level*) to take into account the fact that approval delegation rules state that largest applications from the most creditworthy customers are decided at the highest (and often most distant) hierarchical levels. In addition, we include geographic area fixed effects to capture differences in loan demand and applicant type. In columns (2) and (5) we include the traits of the loan officer responsible for the scoring process (*Gender*, *Age* and *Experience*) and other applicant characteristics, like *Scope of relationship*, *Borrower-to-branch distance* and *Collateral*, that might have an impact on the approval decisions besides the applicant's final rating. In column (5) we also add *Overdrawn*, the share of existing credit at the time of application that is actually used by the applicant, in order to control for possible demand effects. Finally, in columns (3) and (6) we include branch fixed effects. In this case the number of observations is drastically reduced because of missing values and dropped observations because in 6 branches all of the applications were approved. Standard errors are clustered at the branch level or, as the assumption of independence of model errors across branches might be restrictive in the case of granted credit, they are alternatively clustered at the geographic area level.[16]

6.1. *Extensive margin*

When we look at the extensive margin, *Hierarchical distance* between the bank officer responsible for the loan assessment and the bank officer responsible for loan approval has no significant influence on the loan approval decision. In contrast, as expected, risky applicants are less likely to be approved. This negative effect is both statistically and economically significant: using the specification in column (3), the least risky applicants (*Final rating* = 1) have less than 1% probability of being rejected, when other variables are valued at their means, while for the average risky applicant (*Final rating* = 8) the probability of loan rejection is 2.6%, and it becomes 5.5% and 9% for the riskiest applicants (*Final rating* equals to 12 and 15, respectively). In addition, loan applications are most likely (99.9%) to be approved when the decision is made at the highest hierarchical level (*Approval level* = 11), while it decreases to 78% when the approval power is

[15] In order to focus on loan approval decisions, we exclude from the sample of loan applications that reflect an internal credit transfer between the bank and other affiliated banks.

[16] Statistical inference is practically identical using the two different definitions (and number G) of clusters and then computing t-tests and F-tests with G-1 degrees of freedom (Cameron and Miller 2015).

delegated to the branch level. This reflects the approval delegation rules of the bank where loan approval authority for the most creditworthy applicants in terms of size and total exposure, resides at the headquarters or at other high hierarchical levels. Finally, customers with a broad relationship with the bank (*Scope of relationship* = 1) are 6% more likely to see their application approved than applicants with a narrow relationship (99% versus 93%), while applications managed by young loan officers are less likely to be approved (89%, for thirty-eight years old loan officers, versus 99% for those of fifty-six years).

6.2. *Intensive margin*

In columns (4)-(6), we report OLS regression results for the amount of credit granted by limiting the analysis to approved loans. Regression results show that *Hierarchical distance* has a negative and statistically significant impact on the amount of credit granted. The economic effect of the distance between the bank offices responsible loan origination and loan approval is equally significant, with a negative elasticity of extended credit to *Hierarchical distance* that varies from 0.21 (column (3)) to 0.32 (column (3)).

It is interesting to note that the coefficient on *Final rating* is statistically not different from zero, suggesting that once the approval decision is made, the amount of granted credit is unaffected by the assessment of the applicant's risk recommended by the loan officer. In addition, to the extent that approval decisions on largest loans are made at high hierarchical levels, granted credit is positively associated with *Approval level*. Finally, with regard to the other control variables, results in column (3) indicates that loan officer characteristics have no influence on the amount of grated credit, while collateralized loans (*Collateral* = 1) given to companies maintaining broad relationships with the bank (*Scope of relationship* = 1) tend to be larger on average.

6.3. *Extensions and robustness*

6.3.1. *Selection bias*

Since the subpopulation of approved loans may be a non-randomly selected sample of applicants' population, and since the unobserved determinants of the propensity to approve a loan and the amount of granted credit may be correlated, we estimate a Heckman correction model. As excluded restrictions we use the age and job experience of loan officers responsible for the loan appraisal. These variables, as the previous analysis suggests, can be assumed to influence the trust that the manager or the committee responsible for loan approval ascribes to credit scoring recommendations that they receive from loan officers, and are likely to have more of an impact on the loan approval decision than on the amount of credit to extend. In addition, we use *Group belonging* based on the assumption that financing applicants that are part of a large holding group may be more valuable to the bank due to their links to other actual, or potential, borrowers.

Regression results are reported in table 8. The correlation coefficient between the error terms of the selection and main equations is positive and quite large (0.75). The mills ratio λ, with a p-value of 0.12, is slightly below the standard levels of significance. Estimated coefficients on variables of interest are broadly consistent with the previous analysis. A higher *Hierarchical distance* from the loan officer responsible for information and credit scoring production induces the senior bank manager(s) with the approving authority to grant on average a lower amount of credit, while leaving the decision on whether to extend credit largely unaffected at the extensive margin. In contrast, the applicant's *Final rating* has a decreasing effect on the probability to accept a loan application, but it has a statistically insignificant impact on the amount of granted credit. Finally, loans approved at higher hierarchical levels have both a higher probability of approval and larger amount granted.

6.3.2. *Geographical distance at same approval levels*

Two possible concerns related to the previous analysis are the high positive correlation between *Hierarchical distance* and *Approval level* (0.75) and the fact that the bank's approval rule requires that large loan applications be decided at a high hierarchical level. As a result, it can be difficult to isolate the effect of the geographical distance between bank officers at different hierarchical levels from the effect of a pure organizational distance due to the hierarchical layers through which the loan application flows before a final approval decision is made. To address this concern, we follow the strategy suggested by Liberti and Mian (2009) and limit the analysis to loans approved at the hierarchical levels 3 and 4. At these two approval levels the officer responsible for loan origination and the officer responsible for loan approval are sometimes located in the same branch and sometimes located in geographically distant branches.

Results, reported in table 9, are consistent with the hypothesis that the geographical location of officers at different hierarchical levels matter for loan approval decisions. In particular, it is interesting to note that in this case *Hierarchical distance* has a negative and statistically significant impact also on the probability of approving applications. In addition, the magnitude of the adverse effect of *Hierarchical distance* on the amount of credit granted at approval levels 3 and 4 is greater than the average effect of *Hierarchical distance* computed on loans approve at all hierarchical levels (tables 7 and 8).

7. 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 specifically 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 (e.g., Stein 2002, Berger et al. 2005). At the same time researchers have noted that technological innovation may have enabled banks to "harden" soft information (Berger 2015, Udell 2015). This hardening phenomenon could involve a displacement of soft information with hard information and/or a hardening of information that is originally soft when produced by the underwriting loan officer. In this paper we study the latter phenomenon. That is we investigate the extent to which soft information can be "hardened" as part of the credit scoring process. 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 and loan approval decisions on a sample of medium- and large-size commercial loan applications. During the credit process our bank's credit scoring system, like 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 (i.e., well-defined) payoff 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 a well-defined, specific payoff related dimensions and thus could be viewed as a "purer" form of uncodifiable soft information.

Our tests center around the information frictions produced by communicating at distance. If credit scoring does not eliminate communication frictions within the banking organization and soft information cannot be successfully hardened and transmitted across the banking hierarchy, then we should expect that the actual, discretionary use of soft information is affected by the distance between the originating loan officer and the bank headquarters where its activity is assessed. In addition, we should expect that, credit scoring being equal, the distance that separates the bank managers with the loan approval authority from the loan officer responsible for the credit scoring adversely impact on lending decisions.

Summarizing, our results indicate that hardening soft information through credit scoring technology has its limits. That is, credit scoring does not eliminate the barriers to the unbiased communication of soft information across bank hierarchical layers.

First, we find that functional distance matters and that it impacts 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 on the basis of well-defined borrower characteristics and the purer form of soft information involved in the override decision. Specifically, we find evidence that loan officers in branches far from the bank's headquarters are more 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 predisposed by the bank. By contrast, distant loan officers are less likely to override the integrated rating, both upwards and downwards, by transmitting within the hierarchy purer form of soft information. Taken together, these findings suggest that loan officers at branches far from the bank's headquarters exercise discretionary adjustments of automated scores strategically to increase the probability of loan approval thus "gaming" the system to increase the probability of bonuses and career advancement, while they shy away from transmitting subjective notes on applicants that are deeply scrutinized at the bank's headquarters.

Second, we find that firms applying to remote branches receive a lower amount of credit than firms with the same score applying to branches closer to the bank office with final approval authority, thus suggesting that communication frictions due to the distance between bank offices has an impact on the informative value attributed to credit scores. Overall, therefore, our findings confirm the persistence of spatially-based organizational frictions despite the adoption of a modern credit-scoring based lending technology.

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Figures and tables

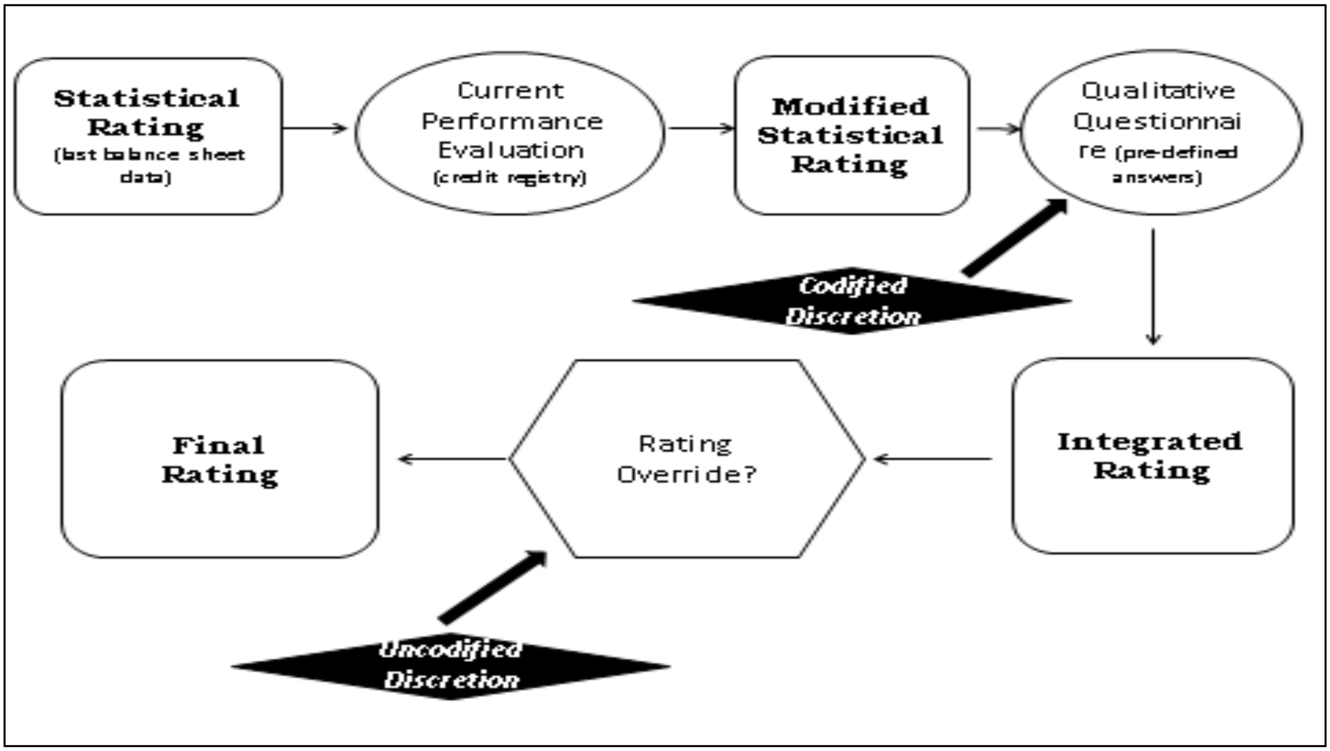


Figure 1. The credit scoring process

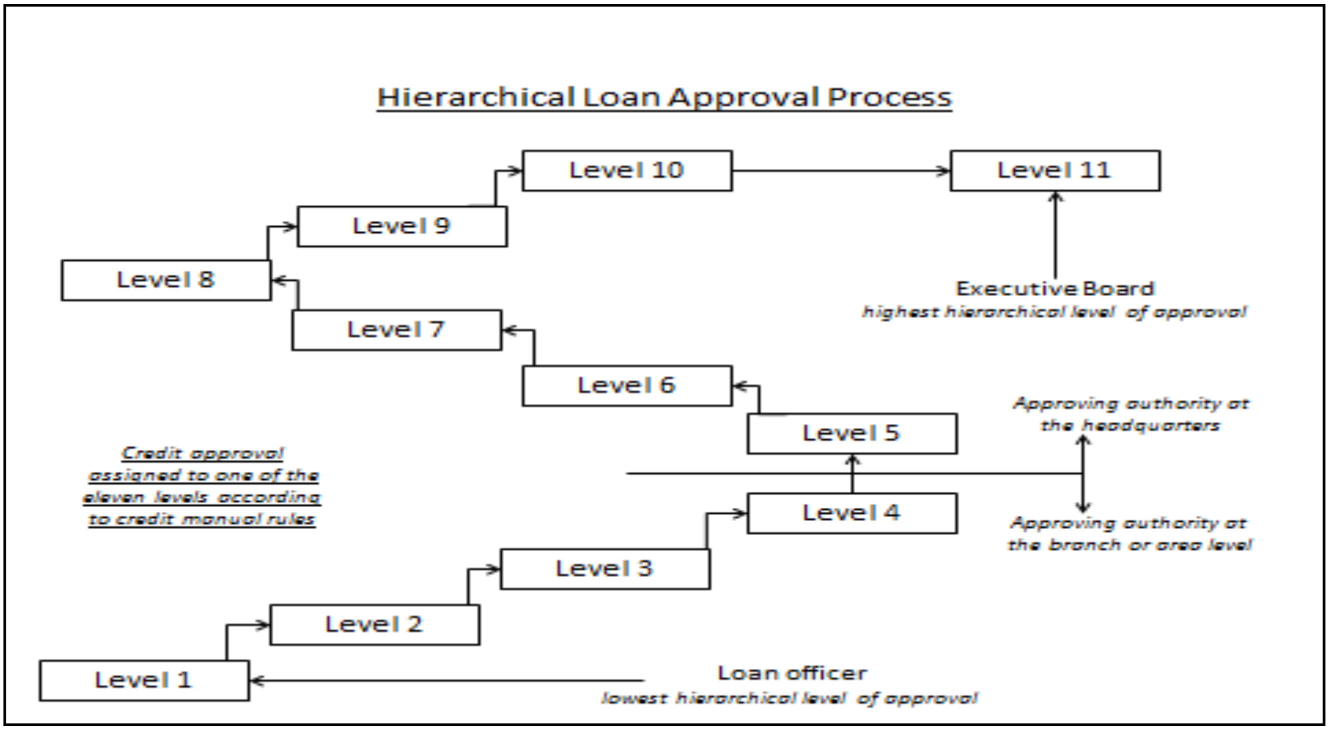
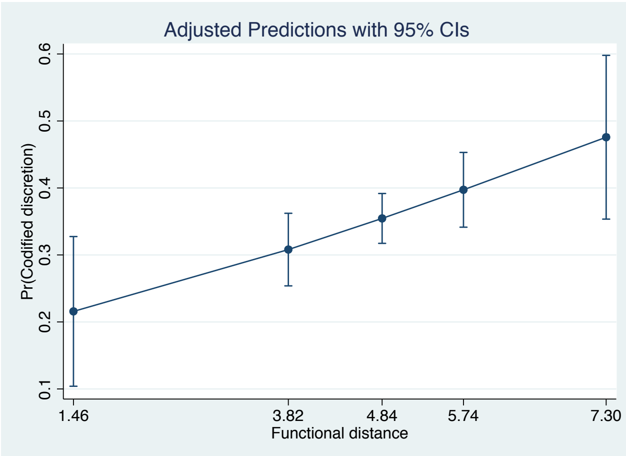
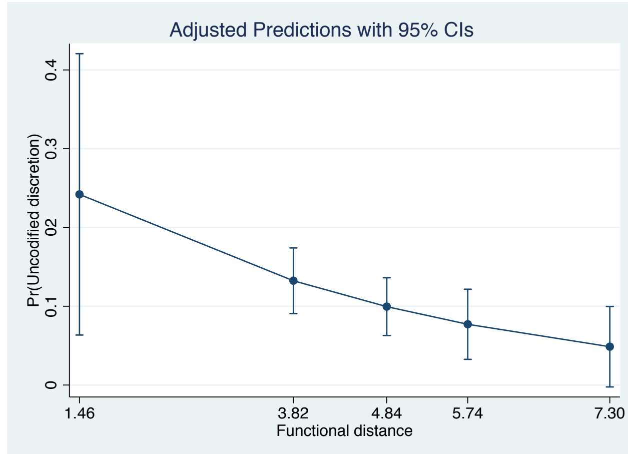


Figure 2. The loan approval process



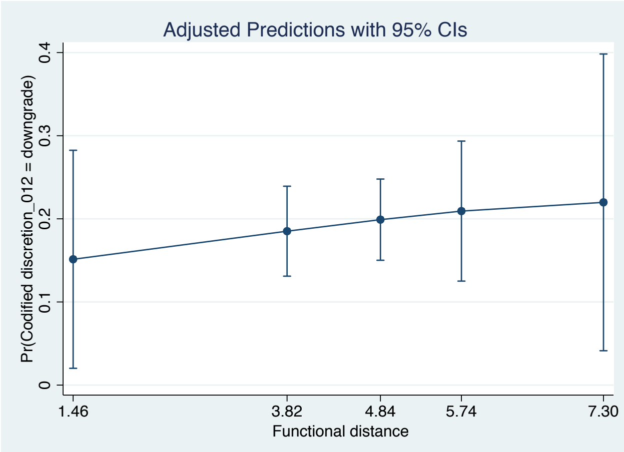
Panel (a): Codified discretion



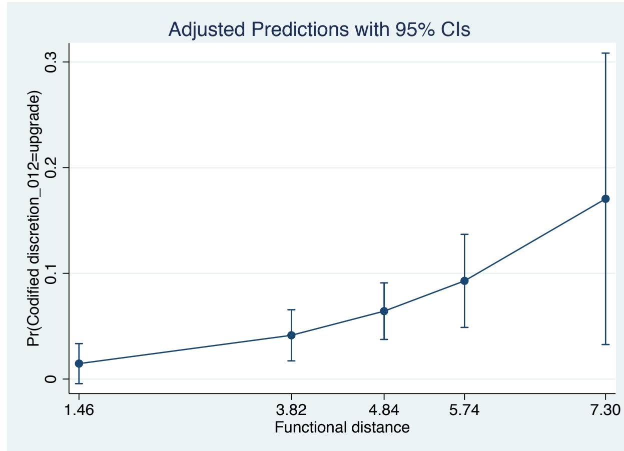
Panel (b): Uncodified discretion

Figure 3. Predicted *Codified discretion* and *Uncodified discretion* at percentiles of *Functional distance*

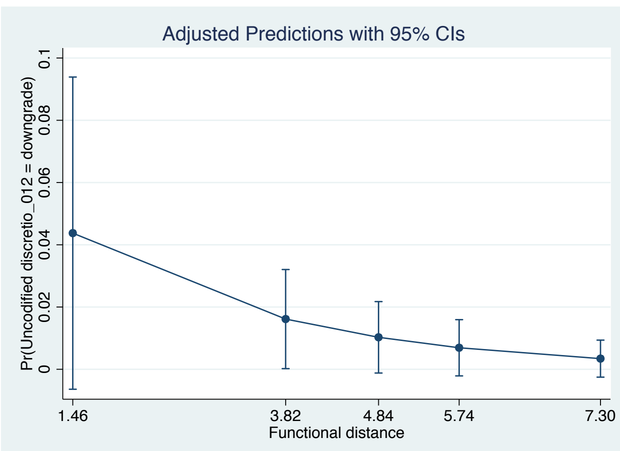
Notes: on the x-axis are reported the10th, 25th, 50th, 75th, and 90th percentiles of *Functional distance* distribution.



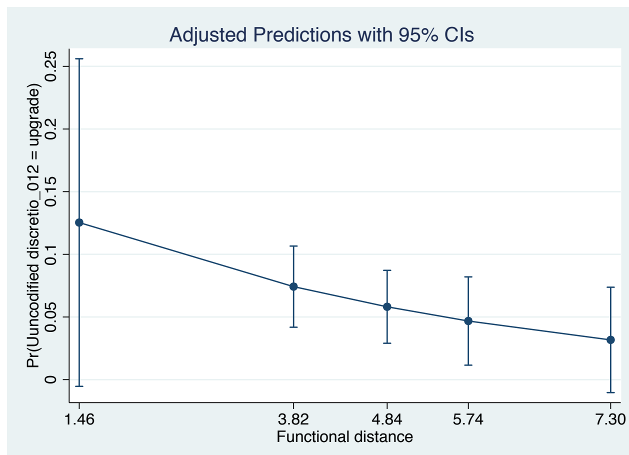
Panel (a): Codified discretion: downgrade



Panel (b): Codified discretion: upgrade



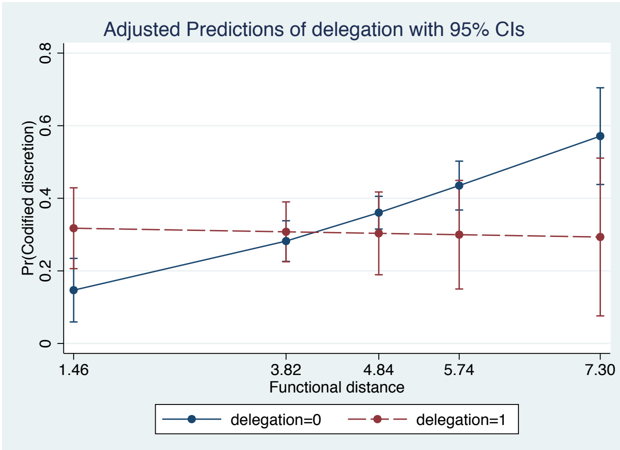
Panel (c): Uncodified discretion: downgrade



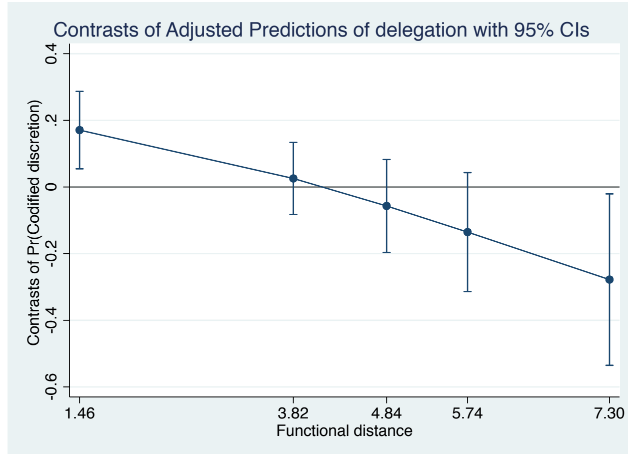
Panel (d): Uncodified discretion: upgrade

Figure 4. Predicted outcomes of *Codified discretion* and *Uncodified discretion* at percentiles of *Functional distance*

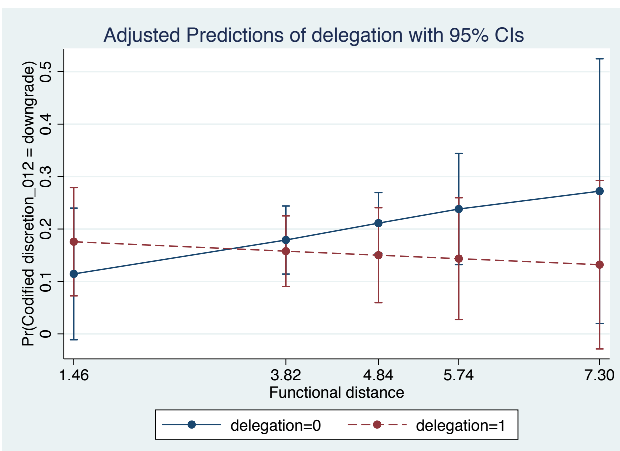
Notes: on the x-axis are reported the 10th, 25th, 50th, 75th, and 90th percentiles of *Functional distance* distribution.



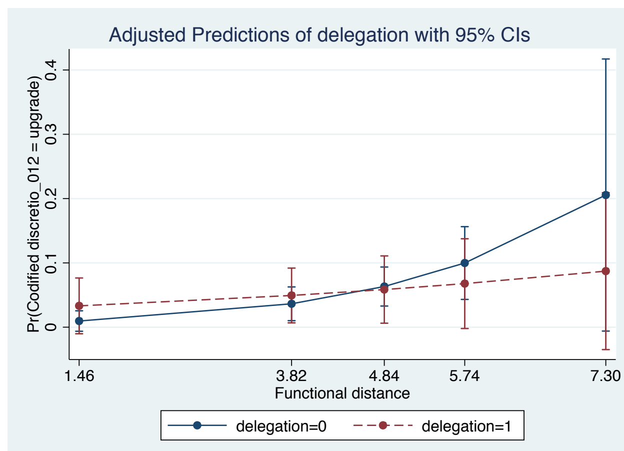
Panel (a): Codified discretion



Panel (b): Contrasts of codified discretion



Panel (c): Codified discretion: downgrade



Panel (d): Codified discretion: upgrade

Figure 5. Predicted outcomes of *Codified discretion* at percentiles of *Functional distance* when loan approving authority is (is not) delegated to loan officers

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

Table 1. Distribution of applicants by approval level and hierarchical distance

	Level of approval											
Same branch	1	2	3	4	5	6	7	8	9	10	11	Total
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			
Total discretion	dummy variable: = 1 if modified statistical rating ≠ final rating	464	0.44	(NA)	0	1
Uncodified discretion	dummy variable: = 1 if integrated rating ≠ final rating	483	0.19	(NA)	0	1
Codified discretion	dummy variable: = 1 if modified statistical rating ≠ integrated rating	464	0.36	(NA)	0	1
*Total discretion_012**	step variable: = 0 if modified statistical rating = final rating; = 1 if modified statistical rating > final rating; = 2 if modified statistical rating < final rating	464 [258 110 96]	0.65	(NA)	0	2
*Uncodified discretion_012**	step variable: = 0 if integrated rating = final rating = 1 if integrated rating < final rating = 0 if integrated rating > final rating	483 [393 28 62]	0.32	(NA)	0	2
*Codified Discretion_012**	step variable: = 0 if modified statistical rating = integrated rating; = 1 if modified statistical rating > integrated rating; = 2 if modified statistical rating < integrated rating	464 [296 99 69]	0.51	(NA)	0	2
Loan amount (million euros)	continuous variable: logarithm of approved credit [absolute values]	478	0.72 [9.95]	1.95 [28.79]	-5.52 [0.004]	6.02 [410,13]
Approved	dummy variable: = 1 if the loan application is approved and 0 it is rejected	550	0.87	(NA)	0	1
			Distance-related Variables			
Functional distance	continuous variable: logarithm of 1 plus the physical distance in kilometers between the branch in which the loan officer responsible for the loan application operates and the bank's headquarters [absolute values]	550	4.60 [290.2]	1.75 [390.4]	1.25 [2.5]	7.30 [1,482]
Hierarchical distance	continuous variable: logarithm of 1 plus the kilometric distance between the branch where the loan officer who conducts the credit scoring operates and the branch of the loan-approving authority [absolute values]	550	2.67 [150.6]	2.59 [294.3]	0 [0]	7.36 [1576]
Borrower-to-branch distance	continuous variable: logarithm of 1 plus the distance between the branch where the loan officer works and the headquarters of the applicant company [absolute values]	550	4.39 [795.7]	2.10 [2523.3]	0.18 [0.2]	9.60 [14753]
			Firm-bank Relationship Variables			
Approval level	discrete variable: ultimate hierarchical level of loan approval *(= 1 if the loan officer has the ultimate loan approval authority)*	550	4.14	2.76	1	11
Gender	dummy variable: = 1 if the loan officer in charge of the loan application is a male	539	0.78	(NA)	0	1
Age	discrete variable: age of the loan officer in charge of the loan application (expressed in years)	520	49	6.14	29	60
Experience	discrete variable: experience of the loan officer within the bank (expressed in years)	520	21	7.95	1	37

Global guarantee	dummy variable: = 1 if the credit lines of a given borrower are backed by a guarantee of the parent company	550	0.15	(NA)	0	1
Collateral	dummy variable: = 1 if the credit line is collateralized	550	0.39	(NA)	0	1
Scope of relationship	dummy variable: = 1 if the borrower purchases at least one other banking product from our bank	550	0.52	(NA)	0	1
Repeated lending	dummy variable: = 1 if there is a prior lending relationship	550	0.94	(NA)	0	1
Related lending	dummy variable: = 1 if the loan application is disciplined ex the Article disciplining the obligations for bank representatives	550	0.02	(NA)	0	1
Group belonging	dummy variable: = 1 if the borrower is part of an economic group (not stand-alone company)	550	0.89	(NA)	0	1
Rating Variables						
Statistical rating	discrete variable: = 1 if the firm has the highest degree of creditworthiness	481	7.44	3.59	1	15
Modified statistical rating	discrete variable: = 1 if the firm has the highest degree of creditworthiness	464	7.35	3.61	1	15
Integrated rating	discrete variable: = 1 if the firm has the highest degree of creditworthiness	483	7.68	3.40	1	15
Final rating	discrete variable: = 1 if the firm has the highest degree of creditworthiness	516	8.02	3.68	1	15
Borrower-specific Controls						
Total assets	continuous variable: logarithm of total firm's assets as stated in the last financial statement *[absolute values of TA]*	472	18.01 *[195,000,000]*	1.78 *[303,000,000]*	12.32 *[224,000]*	21.59 *[2,370,000,000]*
Intangible assets	continuous variable: share of intangible assets over the total assets of the company as stated in the last financial statement	455	0.07	0.11	0	0.62
Long-term debt	continuous variable: share of long-term debt over the total assets of the company as stated in the last financial statement	418	0.15	0.16	0	1.23
Equity ratio	continuous variable: share of equity over the total assets of the company as stated in the last financial statement	472	0.28	0.21	- 0.63	0.96
Credit-specific Controls						
Overdrawn	continuous variable: share of existing credit at the time of application that is actually used by the applicant	504	0.41	0.56	0	5.40
Delegation	dummy variable: = 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	550	0.22	(NA)	0	1

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

Table 3. Logit and multinomial logit regressions of *Total discretion*

	(1)	(2)	
	Logit	Multinomial logit	
		Downgrade	Upgrade
Functional distance	0.036	-0.014	0.187
	(0.107)	(0.145)	(0.137)
Gender	-0.136	-0.174	0.212
	(0.309)	(0.411)	(0.679)
Age	-0.050**	-0.021	-0.071**
	(0.023)	(0.034)	(0.029)
Experience	0.012	0.027	-0.014
	(0.018)	(0.028)	(0.031)
Scope of relationship	-0.405	-0.641*	-0.112
	(0.296)	(0.354)	(0.399)
Repeated lending	-0.122	-0.075	0.372
	(0.589)	(0.643)	(0.731)
Borrower-to-branch distance	0.007	0.037	-0.036
	(0.081)	(0.105)	(0.105)
Approval level	0.095**	0.131**	0.067
	(0.043)	(0.053)	(0.061)
Related lending	-1.666	-0.929	-12.848***
	(1.161)	(1.377)	(0.882)
Modified statistical rating	0.048	-0.096*	0.292***
	(0.045)	(0.053)	(0.086)
Total assets	0.119	-0.121*	0.585***
	(0.082)	(0.070)	(0.196)
Collateral	0.351	0.234	0.563*
	(0.269)	(0.404)	(0.293)
Global guarantee	-0.406	-0.463	-0.383
	(0.376)	(0.367)	(0.590)
Group belonging	0.333	0.032	0.770
	(0.370)	(0.371)	(0.809)
Observations	433	433	433
Area FE	YES	YES	YES
Pseudo R-squared	0.085	0.186	0.186

Notes. In model (1) the dependent variable is *Total discretion*, a binary variable equal to 1 if *Final rating* is different from *Modified statistical rating* and 0 otherwise. In model (2), the dependent variable is *Total discretion_012*, a categorical variable equal to 0 if *Final rating* is equal to *Modified statistical rating*, 1 if the applicant modified statistical rating is adjusted downwards (*Final rating* > *Modified statistical rating*), and 2 if the applicant modified statistical rating is adjusted upwards (*Final rating* < *Modified statistical 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 4. Logit and multinomial logit regressions of *Codified discretion* and *Uncodified discretion*

	Codified discretion			*Uncodified discretion*		
	(1)	(2)		(3)	(4)	
	Logit	Multinomial logit		Logit	Multinomial logit	
		Downgrade	Upgrade		Downgrade	Upgrade
Functional distance	0.204**	0.118	0.474***	-0.313*	-0.462**	-0.261
	(0.096)	(0.164)	(0.166)	(0.171)	(0.186)	(0.210)
Gender	-0.021	-0.135	0.568	-0.881**	-0.344	-0.965
	(0.299)	(0.391)	(0.619)	(0.440)	(1.081)	(0.742)
Age	-0.031*	-0.000	-0.061**	-0.064	-0.149*	-0.041
	(0.017)	(0.029)	(0.030)	(0.040)	(0.082)	(0.047)
Experience	-0.008	0.003	-0.034	0.069*	0.198**	0.030
	(0.020)	(0.026)	(0.032)	(0.035)	(0.099)	(0.039)
Scope of relationship	-0.344	-0.404	-0.245	-0.438	-0.784	-0.301
	(0.246)	(0.287)	(0.324)	(0.435)	(0.791)	(0.375)
Repeated lending	0.024	-0.095	1.049	0.294	-0.292	0.616
	(0.715)	(0.676)	(0.843)	(0.875)	(1.192)	(1.190)
Borrower-to-branch distance	-0.000	0.089	-0.120	-0.092	-0.295*	0.000
	(0.074)	(0.106)	(0.109)	(0.084)	(0.173)	(0.086)
Approval level	0.077	0.093*	0.043	0.083	0.182	0.045
	(0.049)	(0.055)	(0.071)	(0.074)	(0.117)	(0.078)
Related lending	-1.284	-0.603	-13.700***		-15.282***	-15.321***
	(1.212)	(1.530)	(0.657)		(1.143)	(1.039)
Modified statistical rating	-0.046	-0.174***	0.202***			
	(0.035)	(0.047)	(0.064)			
Integrated rating				0.257***	0.150	0.301***
				(0.061)	(0.093)	(0.079)
Total assets	0.073	-0.172**	0.667***	0.065	0.066	0.034
	(0.088)	(0.087)	(0.217)	(0.139)	(0.143)	(0.153)
Collateral	0.051	-0.234	0.462	0.825***	1.652***	0.556*
	(0.324)	(0.434)	(0.365)	(0.314)	(0.424)	(0.337)
Global guarantee	-0.407	-0.471	-0.266	-0.596	-0.780	-0.475
	(0.428)	(0.422)	(0.648)	(0.436)	(0.806)	(0.544)
Group belonging	-0.120	-0.272	0.026	0.987*	0.092	1.426*
	(0.345)	(0.315)	(0.756)	(0.542)	(0.396)	(0.849)
Observations	433	433	433	441	447	447
Area FE	YES	YES	YES	YES	YES	YES
Pseudo R2	0.064	0.18	0.18	0.19	0.222	0.222

Notes. In model (1) 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 model (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 model (3) the dependent variable is *Uncodified discretion*, a binary variable equal to 1 if *Final rating* is different from *Integrated rating* and 0 otherwise. In model (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 5. Logit and multinomial logit regressions of *Codified discretion* and *Uncodified discretion*: the effects of approving authority delegation

	Codified discretion			*Uncodified discretion*		
	(1)	(2)		(3)	(4)	
	Logit	Multinomial logit		Logit	Multinomial logit	
		Downgrade	Upgrade		Downgrade	Upgrade
Functional distance	0.331***	0.224	0.601***	-0.326*	-0.511**	-0.261
	(0.105)	(0.197)	(0.224)	(0.188)	(0.220)	(0.217)
Delegation	1.785***	1.238*	2.155*	0.708	0.162	1.021
	(0.556)	(0.556)	(1.106)	(1.154)	(1.765)	(1.031)
Functional distance × Delegation	-0.347***	-0.267	-0.436*	0.050	0.224	-0.041
	(0.136)	(0.185)	(0.259)	(0.201)	(0.277)	(0.189)
Gender	-0.066	-0.181	-0.484	-0.837*	-0.309	-0.923
	(0.312)	(0.401)	(0.635)	(0.429)	(1.112)	(0.732)
Age	-0.029**	0.000	0.056	-0.063	-0.146*	-0.040
	(0.015)	(0.029)	(0.028)	(0.040)	(0.077)	(0.046)
Experience	-0.011	0.000	0.036	0.068**	0.199**	0.028
	(0.019)	(0.026)	(0.032)	(0.034)	(0.098)	(0.038)
Scope of relationship	-0.325	-0.378	-0.284	-0.398	-0.738	-0.277
	(0.247)	(0.293)	(0.334)	(0.430)	(0.859)	(0.370)
Repeated lending	0.078	-0.053	1.072	0.211	-0.461	0.582
	(0.683)	(0.649)	(0.878)	(0.860)	(1.212)	(1.208)
Borrower-to-branch distance	-0.008	0.100	-0.130	-0.081	-0.271	0.009
	(0.082)	(0.114)	(0.118)	(0.086)	(0.180)	(0.087)
Approval level	0.096*	0.099	0.053	0.157*	0.275***	0.112
	(0.053)	(0.064)	(0.076)	(0.080)	(0.107)	(0.087)
Related lending	-1.309	0.639	-13.24***		-13.707***	-14.198***
	(1.202)	(1.472)	(0.659)		(0.919)	(1.149)
Modified statistical rating	-0.039	-0.168***	-0.207***			
	(0.036)	(0.048)	(0.063)			
Integrated rating				0.265***	0.164	0.310***
				(0.061)	(0.106)	(0.076)
Total assets	0.069	-0.175**	0.645***	0.076	0.085	0.041
	(0.089)	(0.088)	(0.210)	(0.141)	(0.149)	(0.154)
Collateral	0.055	-0.243	0.519	0.803***	1.571***	0.552*
	(0.425)	(0.445)	(0.369)	(0.304)	(0.399)	(0.331)
Global guarantee	-0.413	-0.470	-0.278	-0.618	-0.786	-0.510
	(0.425)	(0.420)	(0.656)	(0.450)	(0.782)	(0.570)
Group belonging	-0.088	-0.276	0.120	1.086**	0.286	1.539*
	(0.345)	(0.309)	(0.767)	(0.533)	(0.220)	(0.217)
Observations	433	433	433	441	447	447
Area FE	YES	YES	YES	YES	YES	YES
Pseudo R2	0.075	0.189	0.189	0.190	0.230	0.230

Notes. In model (1) 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 model (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 model (3) the dependent variable is *Uncodified discretion*, a binary variable equal to 1 if *Final rating* is different from *Integrated rating* and 0 otherwise. In model (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*: additional controls

	Codified discretion			*Uncodified discretion*		
	(1)	(2)		(3)	(4)	
	Logit	Multinomial logit		Logit	Multinomial logit	
		Downgrade	Upgrade		Downgrade	Upgrade
Functional distance	0.285***	0.238	0.536***	-0.704***	-0.996***	-0.765***
	(0.099)	(0.155)	(0.170)	(0.183)	(0.264)	(0.265)
Gender	-0.032	-0.154	0.513	-0.902**	-0.584	-0.661
	(0.321)	(0.454)	(0.667)	(0.424)	(1.042)	(0.811)
Age	-0.017	0.033	-0.073**	-0.123**	-0.302***	-0.109
	(0.019)	(0.030)	(0.032)	(0.059)	(0.094)	(0.071)
Experience	-0.009	-0.006	-0.027	0.097***	0.326***	0.067
	(0.020)	(0.024)	(0.035)	(0.037)	(0.110)	(0.041)
Scope of relationship	-0.309	-0.379	-0.357	-0.463	-0.707	-0.181
	(0.250)	(0.275)	(0.341)	(0.512)	(0.815)	(0.461)
Repeated lending	0.680	0.517	1.343	0.231	1.568	0.409
	(0.705)	(0.747)	(0.817)	(1.038)	(1.298)	(1.068)
Borrower-to-branch distance	-0.035	0.056	-0.115	-0.119	-0.069	-0.002
	(0.077)	(0.116)	(0.105)	(0.112)	(0.189)	(0.123)
Approval level	0.084	0.152**	0.019	0.110	0.219	0.068
	(0.056)	(0.067)	(0.075)	(0.084)	(0.149)	(0.073)
Related lending	-1.185	-0.332	-12.693***		-15.840***	-16.174***
	(1.326)	(1.928)	(0.663)		(1.527)	(1.022)
Modified statistical rating	-0.059	-0.124	0.087			
	(0.049)	(0.076)	(0.074)			
Integrated rating				0.253***	0.273**	0.269***
				(0.095)	(0.132)	(0.103)
Total assets	0.151	-0.169	0.768***	0.167	-0.292	0.370
	(0.118)	(0.116)	(0.268)	(0.208)	(0.366)	(0.309)
Collateral	-0.058	-0.333	0.431	0.736*	2.341***	0.031
	(0.357)	(0.463)	(0.405)	(0.445)	(0.596)	(0.552)
Global guarantee	-0.367	-0.629	-0.088	-0.538	-2.229***	-0.058
	(0.413)	(0.478)	(0.566)	(0.579)	(0.792)	(0.819)
Group belonging	0.183	0.183	-0.062	1.016	1.110	0.848
	(0.425)	(0.436)	(0.765)	(0.655)	(0.715)	(1.088)
Long-term debt	0.102	-0.948	0.468	5.969***	2.882**	7.454***
	(1.178)	(1.615)	(1.445)	(1.402)	(1.329)	(2.287)
Intangible assets	1.030	0.717	0.899	-5.010**	-33.621	-3.400
	(1.150)	(2.028)	(1.834)	(2.473)	(20.710)	(2.381)
Equity ratio	-0.328	1.232	-3.406**	2.406	0.877	3.385
	(0.874)	(1.389)	(1.397)	(2.391)	(3.076)	(2.168)
Observations	379	379	379	374	379	379
Area FE	YES	YES	YES	YES	YES	YES
Pseudo R2	0.071	0.197	0.197	0.298	0.390	0.390

Notes. In model (1) 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 model (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 model (3) the dependent variable is *Uncodified discretion*, a binary variable equal to 1 if *Final rating* is different from *Integrated rating* and 0 otherwise. In model (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 7. Probit and OLS regressions of loan approval

	(1) Probit dy/dx	(2) Probit dy/dx	(3) Probit dy/dx	(4) OLS	(5) OLS	(6) OLS
Hierarchical distance	-0.007	-0.007	-0.001	-0.266***	-0.178***	-0.214***
	(0.006)	(0.005)	(0.006)	(0.058)	(0.056)	(0.071)
Final rating	-0.005*	-0.003	-0.005**	-0.019	-0.017	-0.022
	(0.003)	(0.002)	(0.002)	(0.022)	(0.025)	(0.031)
Approval level	0.026***	0.023***	0.022***	0.367***	0.255***	0.299***
	(0.006)	(0.005)	(0.005)	(0.056)	(0.062)	(0.071)
Gender		0.010	0.025		-0.369	-0.198
		(0.015)	(0.022)		(0.240)	(0.232)
Age		0.004**	0.004**		-0.007	0.000
		(0.002)	(0.002)		(0.017)	(0.021)
Experience		-0.001	-0.000		-0.006	-0.004
		(0.001)	(0.001)		(0.014)	(0.014)
Scope of relationship		0.038**	0.053***		1.284***	1.260***
		(0.016)	(0.018)		(0.230)	(0.281)
Borrower-to-branch distance		0.000	0.005		-0.075*	-0.076
		(0.003)	(0.004)		(0.042)	(0.047)
Collateral		-0.002	-0.004		0.827***	0.697***
		(0.013)	(0.015)		(0.205)	(0.229)
Overdraw					-0.040	-0.066
					(0.221)	(0.215)
Observations	491	464	361	449	391	391
Area FE	YES	YES	YES	YES	YES	YES
Branch FE	NO	NO	YES	NO	NO	YES
R2 - Pseudo R2	0.210	0.266	0.318	0.133	0.303	0.354

Notes. In columns (1)-(3) the dependent variable is *Approved*, a binary variable equal to 1 if the loan is application is approved and 0 it is rejected. In columns (4)-(6) the dependent variable is *Loan amount*, a continuous variable equal to logarithm of the amount of granted credit. All variables are defined in Table 2. In columns (1)-(3), reported coefficients are average marginal effects. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 8. Heckman model regressions of loan approval

	(1) Loan amount	(2) Approved
Hierarchical distance	-0.238***	0.007
	(0.058)	(0.087)
Final rating	-0.023	-0.076**
	(0.024)	(0.033)
Approval level	0.292***	0.313***
	(0.049)	(0.106)
Scope of relationship	1.330***	0.765***
	(0.179)	(0.256)
Collateral	0.685***	-0.055
	(0.172)	(0.255)
Age		0.065**
		(0.030)
Experience		-0.014
		(0.023)
Group belonging		0.379*
		(0.217)
Mills ratio	-0.750	
	(0.632)	
Observations	423	464
Area FE	YES	YES
Branch FE	YES	YES
rho	-0.490	

Notes. In column (1) and (2) the dependent variables are, respectively, *Loan amount*, a continuous variable to logarithm of the amount of granted credit, and *Approved*, a binary variable equal to 1 if the loan is application is approved and 0 it is rejected. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.

Table 9. OLS regressions of loan approval: approval levels 3 and 4

	(1) OLS	(2) OLS	(3) OLS
Hierarchical distance	-0.274***	-0.287***	-0.361**
	(0.059)	(0.064)	(0.161)
Final rating	-0.090**	-0.031	-0.082
	(0.039)	(0.055)	(0.079)
Approval level	0.312	0.865**	0.990**
	(0.411)	(0.379)	(0.447)
Scope of relationship		1.157***	1.271***
		(0.301)	(0.369)
Borrower-to-branch distance		-0.138	-0.014
		(0.095)	(0.140)
Collateral		0.637*	0.275
		(0.345)	(0.451)
Overdraw		0.407	0.559
		(0.353)	(0.436)
Observations	126	114	114
Area FE	YES	YES	YES
Branch FE	NO	NO	YES
R2	0.175	0.369	0.535

Notes. The dependent variable is *Approved*, a binary variable equal to 1 if the loan is application is approved and 0 it is rejected. Standard errors, in brackets, are clustered at the branch level. *** p<0.01, ** p<0.05, * p<0.1, respectively.