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The effect of delegation of decision rights and control: The case of lending decisions for small firms

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ABSTRACT

We examine the effect of the allocation of decision rights on loan outcomes using proprietary data from a bank. Given that loan officers accumulate soft, nonverifiable information about borrowers through repeated interactions over time, our bank grants decision rights on some loans to loan officers. For larger and risky loans, the bank centralizes decision rights to assure that those loans are diversified across industries. When loans require approval from higher-level officers, loan officers must communicate their accumulated information with higher-level officers. Given that loan officers are incentivized to make loans irrespective of who has the discretion to grant the loan, internal disclosure of soft information appears to come at a cost. Relative to loans where loan officers have discretion, loans that require approval from higher hierarchical levels feature: (1) greater discounts on standard loan rates, and (2) a greater likelihood of a loan quality downgrade in the period following approval. Our evidence suggests that the incentive for loan officers to make loans, in combination with the necessity for higher ranked-officers to rely on soft information in their loan decisions, creates conditions in which information reported by loan officers may become optimistically biased.

1. Introduction

Principals may have formal authority, but this does not necessarily imply that they have real authority. Given that lower-level agents collect private information on local customers and markets that is valuable for decision making, real authority over decisions in many cases resides with lower-level agents. To ensure that local information is utilized in decisions, firms often delegate formal authority to agents (Jensen and Meckling, 1992; Aghion and Tirole, 1997) and use Management Control Systems (MCS) to enhance the likelihood that agents will make decisions congruent with firms' objectives. Centralization of formal authority affects the communication between lower-level agents and the firm if the objectives are sufficiently incongruent; agents are concerned that their decisions will be overruled when principals become better informed (Aghion and Tirole, 1997). This study examines the effects of the allocation of decision rights on decision outcomes.

Our study is set in a bank specialized in the provision of small business credit. Lower-level loan officers are privately informed about the quality of borrowers; they acquire soft, nonverifiable information[1] through their long relationships with customers over time (Boot, 2000). Given the limited supply of hard information, the soft information that loan officers collect is especially valuable for lending decisions involving small businesses (Agarwal and Hauswald, 2010).[2] Although scant accounting research has been performed on soft, nonverifiable information, the extant literature has however focused on the *external* disclosure of nonverifiable information. For example, Michels (2012) finds that increased voluntary disclosure of nonverifiable information on a peer-to-peer lending website is associated with lower loan rates and increased bidding activity on personal loans. Our study takes issue with the *internal* use of soft information. To do so, we compare loan-decision outcomes in which loan officers must transfer their accumulated soft information to higher-level officers (centralized loan decisions) with loan-decision outcomes in which loan officers directly apply the soft information they have acquired for their own loan decisions (decentralized loan decisions).

Within banks, the partitioning of decision rights on loans typically occurs on the basis of credit risk and the amount of debt (Baker, 2000). Because of the costs of communicating soft information, banks give their loan officers decision rights to approve loans featuring smaller credit risk and total debt (Liberti and Mian, 2009). However, loan

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[1] In this paper, we use the terms 'soft' and 'nonverifiable' interchangeably.
[2] In many cases, small firms are not legally required to produce audited financial reports and are not monitored by external rating agencies.

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officers need to run loan applications featuring larger credit risk and total debt through higher-level officers for approval. When higher-level officers are granted decision rights, loan officers must communicate their accumulated hard and soft information up through the hierarchy by means of a loan file. Transferring local, soft information to higher-level officers may be costly. The nonverifiable nature of the private information enables loan officers to communicate with an optimistic bias that serves their own interests (Hölmstrom, 1984; Gneezy, 2005; Gibbons et al., 2013).

We examine two lending decision outcomes that should reflect the optimistically biased communication of loan officers: loan rate deviations and loan quality adjustments. We use proprietary data from one branch of a major Northern-Western European bank. Our bank determines standard loan rates solely based on verifiable, hard information impounded in the credit risk ratings and total outstanding debt (e.g., personal income, prior defaults, liquidity of receivables). In some cases, the bank may decide to deviate from the standard loan rates. Loan rate deviations involve premiums or discounts on the standard loan rates based on soft information that resides with loan officers (e.g., subjective assessment of the competence of management, feasibility of business plans) and that is not used to establish the standard loan rate. To examine whether loan rate decisions differ contingent on whether the loan officer or a higher-level officer decides on the loan, our first empirical measure is the deviation from standard loan rates. The Loan Quality Code (LQC) measures the likelihood that the borrower will experience difficulties meeting its short-term obligations. The initial LQC is determined when the loan is approved and is reexamined one year later. We assess the extent to which soft information about the loan quality is accounted for at the time of the loan approval. To examine whether quality assessments differ contingent on whether the loan officer or a higher-level officer decides on the loan, our second measure is the likelihood of a LQC downgrade in the year following loan approval.

Our findings suggest that the bank's internal decision structure affects the outcome of loan decisions. We find that loans that are moved up in the hierarchy for approval vis-à-vis loans that are approved by loan officers themselves (1) are offered greater discounts, and (2) are more likely to face a loan quality downgrade in the year following approval, while controlling for, amongst others, the internal risk score and total debt. We argue that our findings of greater discounts on standard loan rates and the greater likelihood of loan quality downgrades when loans require approval from higher-level officers are explained by optimistically biased communication. Loan officers have incentives to make loans and have the opportunity to communicate optimistically with higher-level officers given the nonverifiable nature of their private information. Hence, loan officers can increase the likelihood of loan approval for loans they think should be granted by communicating about the loan quality in an optimistically biased manner (Holmström, 1984; Crawford and Sobel, 1982; Gibbons et al., 2013). Subsequently, we find the relation between higher-level decision making and loan rate deviation to be especially pronounced when the prospective borrower is not legally required to produce audited financial reports. This coincides with the intuition that for firms with audited accounting information, lending decisions are more based on hard, verifiable information which limits the proceeds for loan officers to present soft information optimistically (Liberti and Mian, 2009). As a robustness check, we use a regression discontinuity design by which we compare a subset of loan files just below or above the threshold that distinguishes whether loans have been approved by loan officers or require higher-level approval (i.e., loan files are relatively similar in credit risk and outstanding debt). Our inferences are not affected.

Our evidence does not mean that the bank's decision making is non-optimal. Facing the trade-offs between soft information accumulated by loan officers, incentives for loan officers to originate loans, and the need for higher-level coordination of large and risky loans across industries, the outcome we observe is likely to represent a second-best outcome (Berger and Udell, 2002).

We believe that one main contribution of our paper resides in the fact that the data we collect allows for an empirical examination of the effects of organizational design. Although extant accounting research has built its arguments on the idea that decision making is affected by the design choice of centralization vs. decentralization (e.g., Abernethy et al., 2004; Indjejikian and Matějka, 2012), little *empirical* research has examined whether and how the allocation of decision rights affects decision making. To our knowledge, this paper is one of the few empirical studies to focus on the question of how the transmission of information between hierarchical levels under centralization may affect actual decision making. To this end we build on the work of Dessein (2002) who modeled the trade-off between distortion that arises when agents' decisions are incongruent with those of the principal (under delegation) and distortion when agents inform the principal imperfectly about local information (under centralization). Our results provide an empirical illustration of how, absent the need for coordination of higher and risky loans at higher hierarchical levels, greater discretion for lower-level employees may be called for in a setting in which employees are privately informed and that information cannot be communicated in a verifiable manner.

Our paper also contributes to recent studies in accounting that examine the effect of discretion on employee decision making. For example, Campbell (2012) shows that employees who are allowed to overrule 'predefined rules' make better decisions than employees who comply with predefined rules in making consumer loans. Our findings suggest that centralization makes officers inclined to communicate their soft information more optimistically, as compared to when loan officers themselves are allowed to make loans. In the latter situation it seems that loan officers make more accurate use of their private information.

Finally, our paper complements recent accounting studies that have shown that the external disclosure of nonverifiable information affects investor decision making. Our results suggest that their private, nonverifiable information enables loan officers to actually affect the loan decisions of higher-level officers.

2. Literature review

2.1. Allocation of decision rights

Principals may have formal authority over decisions, but this does not necessarily imply that they have real authority. Given that agents often possess private information valuable for those decisions, real authority in many cases resides with the agent. Formal authority implies that principals can reverse decisions taken by agents by acquiring information but will refrain from doing so when the misalignment of objectives between principal and agent is not too severe (Aghion and Tirole, 1997). The delegation of formal authority increases employee incentive to collect information because it prevents the principal from overruling the agent and, therefore, ensures that collected information will effectively be used in decision making (Aghion and Tirole, 1997). Campbell (2012) indeed documents improved decision making when employees are allowed to overrule 'predefined rules' for granting consumer loans. When principals retain formal authority, the likelihood that the principal will overrule the agent decreases with, amongst others, the required speed of decision making (Dessein, 2002; Alonso et al., 2008) and a large span of control. Centralization of formal authority may affect the communication between principals and agents when their objectives are sufficiently incongruent as agents are concerned that decisions might be overruled when principals become informed (Aghion and Tirole, 1997). Crawford and Sobel (1982) show theoretically how, in a situation in which agents possess private information and the preferences of the agent and principal are not perfectly aligned, agents attempt to manipulate principals when they try to elicit information from them. In equilibrium, when the misalignment of preferences is not too severe, some information can still be revealed in the communication process. The potential for agents to misrepresent their private information crucially depends on whether their private information is nonverifiable (Gibbons et al., 2013).[3]

2.2. Hypothesis development

Banks are a primary supplier of finance for private firms. However, private firms may be informationally opaque in the sense that they typically have a limited supply of hard, verifiable information. This suggests that lending decisions also require other information sources to evaluate a prospective borrower's ability to repay a loan. Relationship banking is one means of resolving problems of asymmetric information between banks and borrowers. Loan officers play an important role as they collect borrower-specific, proprietary information through multiple interactions with borrowers over time (Boot, 2000). With respect to the important role of the loan officer as liaison between borrower and lender, Drexler and Schoar (2014) show how borrowers whose loan officers are on leave are less likely to receive new loans from their bank. Overall, small business lending decisions are typically based on a mix of hard, verifiable information and soft, nonverifiable information (Liberti and Mian, 2009; Hertzberg et al., 2010).

Loan decisions may require approval from higher-level officers because this enables banks to coordinate their loan portfolios such that their exposure to large and risky loans is sufficiently diversified across industries (Diamond, 1984; Acharya et al., 2006).[4] Rossi et al. (2009) find for their sample of large Austrian commercial banks that loan portfolio diversification across size and industry reduces the realized risk of banks and increases their profitability. However, when a loan file needs to be approved by higher-ranked officers, loan officers have to communicate their accumulated information on the risk-return characteristics of the prospective loan. Given that banks provide incentives to loan officers to make loans (Baker, 2002; Campbell, 2012),[5] moral hazard may limit the effectiveness of communication within banking organizations. Heider and Inderst (2012) describe the tension between incentivizing loan officers to originate loans and the communication of soft information. Hertzberg et al. (2010) empirically demonstrate that officers, during post-lending monitoring, include an optimistic bias in their reports about the repayment prospects of borrowers.

In response, principals may decide to increase the weight on hard information and decrease the weight on soft information in the communication between agents and principals when agents seek approval upwards in the hierarchy (Liberti and Mian, 2009). Minnis (2011) expects auditors to play an important role in 'hardening' information and indeed finds that audited information is more strongly by lenders in their decision making. Allee and Yohn (2009) find that audited information increases the access to credit for small, privately held firms. Given that relationship banking provides banks with crucial, nonverifable information on small business creditworthiness, and that verifiable information is in limited supply, soft information may play a role in lending decisions. Cassar et al. (2015) finds that especially firms with a limited supply of soft information (e.g., without long-term relations with lenders) benefit from the supply of sophisticated accounting information based on accrual accounting in terms of lower loan rates.

We argue that it is a priori unclear whether higher-level officers are able to cancel out any optimistic bias from the information provided to them by loan officers. Given that small firms are characterized by a relatively smaller supply of hard, verifiable information, this necessitates soft, nonverifiable information being included in the decision-making process to some extent (Stein, 2002; Berger et al., 2005). Given the less verifiable nature of soft information, it is difficult for higher-level officers to discern biased from unbiased information. Standard economic models assume that individuals are rational Bayesian information processors able to unravel bias incorporated in managerial communication. However, insights from behavioral economics suggest that the optimistically biased communications of loan officers may serve as an anchor for higher-level officers. Despite subsequent adjustments for the possibly optimistic bias of loan officers, an adjustment may be insufficient in the sense that the final loan decision is closer to the anchor than it would have been if the higher-level officers had not been 'anchored' by the optimistic communications of loan officers (Tversky and Kahneman, 1974). Prior research suggests that experts are also susceptible to anchoring, and that it is difficult to correct for this. For example, task familiarity is not sufficient to avoid anchoring (Northcraft and Neale, 1987).

Higher-level decisions on loans can be made by groups of experienced executives, e.g., a credit committee. The inclusion of multiple higher-level officers can broaden the range of available information and therefore may reduce the susceptibility to bias. For example, decision making in groups is shown to increase information-processing capacity and decrease the likelihood that decisions are based on erroneous assumptions (Radner, 1993; Stasser et al., 1995). On the other hand, group mental models may subject groups to the same information-processing biases as individual decision makers (Schwenk, 1986). Information consistent with the group mental model may be easily absorbed while information held by only one group member may not be incorporated into the decision process. In other words, groups tend to only process information that is commonly held instead of the sum of information held by all individuals. Furthermore, the exchange of arguments in a group discussion in support of individual preferred choices may lead to even more polarized opinions from individual members following the group discussion (Barber et al., 2003). Whyte and Sebenius (1997) compared individual and group decision making and found anchoring effects that were similar across groups and individuals.

Our arguments lead to the following hypothesis.

H1. Outcomes on lending decisions are dependent on the hierarchical level of decision making.

3. Research method

3.1. Research setting

3.1.1. Internal organization

Our research site is an individual branch of a well-known Dutch bank.[6] This branch is internally organized in 3 responsibility centers,

[3] In the case of verifiable information, the sender cannot misrepresent, but only withhold information (Grossman, 1981).

[4] This may be at the expense of post-lending monitoring effectiveness when loans become dispersed over industries.

[5] Baker (2000) argues that banks incentivize loan officers based on the number of loans they make rather than on subsequent loan performance. This reduces the risk imposed on loan officers while allowing for potential distortion of the incentive contract.

[6] The external validity of our study could be questioned given that we study only one branch of a bank. We believe that our sample bank qualifies as a solid bank and that the branch features no special characteristics. In 2009, the bank ranked 27th in the world on the basis of total assets with a total assets figure of $840 billion. Our bank is organized through independent branches which foster small-business lending in their local communities. The specific branch that represents our research setting has assets of about $3 billion. The ratings agencies consistently rank our bank at the highest levels; the bank was one of the major banks that did not need any form of bailout throughout the crisis. The bank's tier 1 capital amounts to 17%, while the Basel requirement is 9%. The central office of the bank conducts annual internal audits focused on monitoring operational risks (including legal and reputational risks). Operational audits are preceded by Risk Control Self Assessments for each branch that, amongst others, focus on compliance with firm-level procedures. Inconsistencies when the risk management system is not aligned with the branch's risk exposure result in branches being put under special surveillance, thereby limiting their authority. The branch exhibited no such inconsistencies during the sample period.

i.e., *Business, Retail, and Services*. Our focus is on the *Business* unit that is organized in three front office sections: a small-business, medium-business, and large-business section. The three sections are administratively supported by the back-office. Our research sample comprises 374 approved loan requests issued between January 1, 2008 and July, 31 2009.[7] The small-business and medium-business sections deal with financing requests in which the total debt outstanding in general does not exceed €5 million. This section is composed of six loan officers and their support staff. The large-business section serves firms with greater financing needs and greater complexity, with total debt outstanding typically exceeding €5 million. The section is composed of three loan officers and their support staff. In addition, the section includes two credit analysts who in conjunction with activities in the large-business section also assist teams in the medium-business section when required. Each corporate borrower is assigned a specific loan officer who acts as the liaison between the bank and borrowing firms. On average, loan officers serve 60 companies. The sections each have their own manager who reports to the manager of the Business unit. The Services unit includes a Credit Risk Management section.

3.1.2. *Loan approval process: information collection and analysis*

The loan decision process involves a number of stages. Each firm is assigned a loan officer who serves as the account manager for the respective firm. As their account manager, the loan officer is also responsible for the loan application process. The loan application process starts with the collection of hard information on the nature of the business (activities, products and/or services), current debt (current repayment terms and interest payments), income statement, balance sheet and cash flow statements over the current and prior years (to determine the debt service capacity ratio defined as the non-committed cash flows divided by interest and repayment terms, persistence of profits, sources of cash, etc.), credit ratings, the personal credit history of the owners (personal income, debt, prior defaults), balances from transaction accounts (as our sample bank represents the main banking relationship for most borrowers) and the appraised value of collateral such as fixed assets. This information is entered into a computer system that provides loan officers with an internal risk score (the probability of default) and the loss given default (the inverse of the degree in which the debt is secured by collateral). The probability of default and the loss given default serve as input in the credit scoring methodology to produce the overall credit risk rating (internally referred to as the 'Expected Loss' rating). The credit risk rating is a rating that ranges between 1 and 14 whereby a higher rating corresponds with a higher credit risk.[8] The standard loan rate comprises the purchase rate with a mark-up. This size of the mark-up is based on the internal credit risk rating and the size of the outstanding debt after approval of the loan application. Standard loan rates are increasing in credit risk and, within each credit risk category, decreasing in the amount of debt.[9] Table 1 provides an overview of the computation of the standard loan rate.[10]

In addition, the system generates a Loan Quality Code (LQC) on the basis of the firm's current financial performance and position as well as on its short-term financial prospects to assess the probability that the firm will experience difficulties in meeting short-term obligations towards employees, suppliers of goods and financing, etc. LQC's are determined for new loans as well as updated for existing loan portfolios. One year after a loan has been granted, the bank re-establishes the loan quality code.[11]

Given the focal role of loan officers in integrating all available hard and soft information, as well as their intimate knowledge about the owner, loan officers can include soft information in their loan files. The soft information could involve the quality of business plans, the business case, how the loan contributes to achieving the goals outlined in the business plan, qualifications of the owner (education, industry experience, capabilities and skills as a business owner), integrity, personal investments in the business, etc. Favorable soft information is considered to affect the likelihood of attaining better loan terms such as a discount on the standard loan rate.

3.1.3. *Decision rights*

As account manager for the corporate borrower, a loan officer negotiates the conditions underlying the prospective loan with the client. In some cases, loan officers are not assigned decision rights for loan approval, but these ratification rights are instead restricted to higher-level officers. The assignment of decision rights to higher-ranked officers is contingent on the internal credit risk rating and the outstanding debt. When higher-level approval is required, the loan officer submits the loan file including the hard and soft information prescribed as well as the loan terms as proposed by the loan officer.

With respect to the partitioning of decision rights, we distinguish three different levels. At the first level, the decision rights for loan approval are delegated to the individual loan officer. When a loan officer decides that it is required that the bank deviate from the standard loan rate, she has to run this proposal by the supervisor, i.e. the respective business-section manager. At the second level, decision rights with regard to loan approval are assigned to the credit risk manager (in a few cases assisted by the loan officer's business-section manager). At the third level, decision rights are assigned to the credit committee. This applies when the outstanding debt is relatively large, the credit risk rating is relatively large, or the LQC is VC, ED, or D. Table 2 provides an overview of criteria used to determine the appropriate decision level. The credit committee is composed of the managers of the medium-business and large-business sections, the manager of the Business unit, credit risk managers, and the managing director of the branch. The credit committee meets on a more or less regular basis. Loan decisions made by the credit committee are binding.

3.1.4. *Monitoring of approved loans*

As a final stage of the loan approval process, a control plan is composed including requirements and conditions imposed on the client firm following granting of the new loan. Companies are obliged to periodically disclose information about their financial performance, overviews of debtors, current and non-current liabilities, etc. In addition, the control plan indicates when the loan should be audited to see whether the conditions underlying the loan agreement need to be revised. Both the degree of disclosure and the timing of possible revisions are contingent on the credit risk to which the bank is exposed. Typically, such revisions are executed on an annual or biannual basis.

[7] Our sample period partly coincides with the credit crisis. However, the downturn in the economy was concentrated in later years. For example, unemployment (number of bankruptcies) {retail sales where 2010 = 100} was 6.3% (9.2K) (99.0) in 2006, 4.6% (6.8K) {105.5} in 2008, 5.5%, (10.7K) {100.1} in 2009, 7.1% (11.3K) {99.3} in 2012, and 8.9% (12.5K) {97.2} in 2013 with slow improvement in the Netherlands in the following years (Central Bureau of Statistics).

[8] Client firms with large outstanding debt, high credit risk rating, or an LQC of Vulnerable continuity (VC), Emerging discontinuity" (ED) or "Discontinuity" (D) face supplemental analyses such as the collection of more years of prior financial information, month-to-month cash flow analysis, more extensive screening of the financial condition and history of the principal owner, etc.

[9] The association between larger loans and lower loan rates can, amongst others, be explained by the dilution of contractual and operational fixed costs (Cerqueiro et al., 2011),

[10] As standard loan rates are considered proprietary information, we have added a non-negative number between 0% and 1% to cells.

(*footnote continued*)

[11] Companies with an LQC of "ED" or "D" are reassigned to the Credit Risk Management Section. This section typically imposes additional conditions on the firm (e.g., additional pledges) and, if the firm's financial position deteriorates, takes actions to secure the pledges.

Table 1
Computation standard loan rates.

	Total outstanding debt (× €1000)											
Credit risk rating	0–25	25–50	50–100	100–200	200–500	500–1000	1000–2,000	2000–3,000	3000–5000	5000–10,000	10,00–20,000	≥20,000
1	3.50%	2.90%	2.40%	2.00%	1.65%	1.40%	1.25%	1.20%	1.20%	1.20%	1.15%	1.15%
2	3.55%	2.95%	2.45%	2.05%	1.70%	1.45%	1.35%	1.35%	1.35%	1.30%	1.15%	1.15%
3	3.60%	3.05%	2.55%	2.05%	1.70%	1.45%	1.35%	1.35%	1.35%	1.35%	1.25%	1.20%
4	3.80%	3.20%	2.65%	2.15%	1.80%	1.50%	1.40%	1.40%	1.35%	1.35%	1.30%	1.25%
5	4.00%	3.40%	2.70%	2.30%	1.80%	1.65%	1.55%	1.55%	1.40%	1.40%	1.35%	1.30%
6	4.20%	3.60%	3.00%	2.35%	1.95%	1.75%	1.55%	1.50%	1.45%	1.40%	1.35%	1.30%
7	4.75%	3.70%	3.10%	2.50%	2.15%	1.95%	1.75%	1.70%	1.70%	1.65%	1.65%	1.60%
8	5.40%	4.40%	3.30%	2.80%	2.45%	2.20%	2.05%	2.05%	2.00%	2.00%	1.95%	1.90%
9	5.40%	4.55%	3.70%	3.25%	2.80%	2.60%	2.40%	2.30%	2.25%	2.20%	2.20%	2.20%
10	5.40%	4.80%	4.20%	3.65%	3.20%	2.90%	2.75%	2.60%	2.60%	2.55%	2.55%	2.55%
11	5.40%	5.40%	4.90%	4.30%	3.80%	3.55%	3.25%	3.10%	3.00%	2.90%	2.85%	2.80%
12	5.40%	5.40%	5.40%	5.15%	4.75%	4.50%	4.30%	3.90%	3.70%	3.50%	3.50%	3.50%
13	5.40%	5.40%	5.40%	5.40%	5.15%	4.90%	4.90%	4.90%	4.90%	4.90%	4.90%	4.90%
14	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%	5.40%

Table 2
Delegation of decision rights.

Level	Loan approval	Loan rate	Total outstanding debt	Credit risk rating	Loan Quality Code (LQC)
1	Loan officer	Manager business section	≤ €250.000	EL1-EL14	–
			≤ €600.000	EL1-EL8	–
			≤ €800.000	EL1-EL3	–
2	Credit risk manager (in a few cases assisted by manager Business section)	Manager business section	€250.000–€500.000	EL9-EL14	–
			€500.000–€600.000	EL9-EL14	–
			€600.000–€1.000.000	EL4-EL11	–
			€1.000.000–€2.000.000	EL1-EL11	–
			€2.000.000–€3.000.000	EL1-EL11	–
3	Credit committee	Credit committee	€600.000– €3.000.000	EL12-EL14	–
			≥ €3.000.000	EL1-EL14	–
			≥ €0	EL1-EL14	KWC, DD, D

Besides the scheduled revisions, a revision process can be triggered when interest or principal amount payments are missed. In all cases, the loan officers are responsible for the monitoring of loan agreements, and for potential revisions to loan agreements. Only in the infrequent cases in which the LQC is ED or D is the monitoring of those loans transferred to the Credit Risk Management section. Each branch is audited by the central office regarding the compliance to firm-level procedures regarding monitoring of approved loans.

3.1.5. *Incentives*

Loan officers are eligible for an annual bonus of up to 12% of their salary. The bonus is contingent on individual output measures and group output measures, with only minor changes in the choice of measures across the years.[12] Individual output measures include the amount of new loans granted, the number of new customers served, the number of customers for which the branch serves as the main banking relationship, and specific targets in the area of customer relationship management and credit risk management. Group output measures include accounting performance, the number of new clients in targeted business segments, customer satisfaction, and the number of days needed to address a new financing request. Both individual and output targets are weighted equally in determining the bonus, and the computation of the annual bonus is formula-based. In addition, loan officers are awarded annual salary increases of up to 6% of their salary contingent on individual output measures and subjective assessment of the loan officer's competence. With regard to the subjective assessment, qualitative targets are set based on six dimensions: customer focus, cooperation, result-orientation, pro-activeness, commercial orientation, and quality orientation. Both the objective output measures and the subjective competence measures are equally-weighted in determining the salary increase. The emphasis on loan origination in the whole of loan officer incentives coincides with literature that shows how banks incentivize loan officers based on the number of loans they make rather than subsequent loan performance. This represents the trade-off between risk and distortion in incentive plans in which the emphasis on loan origination reduces the risk imposed on loan officers (as many things beyond the control of loan officers can happen involving lenders following loan approval) while allowing for potential distortion of the incentive contract (Baker, 2000).

The incentives of higher-level officers are designed to reflect the inherent tension between sales and risk. Higher-level officers are evaluated on measures such as branch profitability, the number of new clients, and sales relative to peer banks, as well as on measures that reflect the risk dimension of the business such as outcomes on internal audits, overdrafts on credit lines, missed payments, and the outcome of a risk profile assessment on the loan portfolio. Branch managers are evaluated on, amongst others, branch profitability, asset growth, impairments, and outcomes of internal audits.

3.2. *Empirical models*

Our analyses focus on two empirical measures of loan decisions that should reflect the optimistically biased communications of loan officers. The first dependent variable is the deviation from the standard loan rate, as the risk-return characteristics of a loan appear in the loan rate the bank establishes. Therefore, we regress the deviation from the

[12] For example, only in 2008 was a measure introduced that measured the degree to which their client portfolios were subjected to new, more rigorous ID verification standards to comply with new regulations.

standard loan rate on the decision structure of the bank:

$$\text{RATE\_DEV}_i = \beta_0 + \beta_1 \ \text{CREDRSK\_MGR}_i + \beta_2 \ \text{CRED\_COM}_i + \text{CONTROLS}_i + \varepsilon_i, \quad (1)$$

where RATE_DEV_i denotes the actual deviation from the standard loan rate as a percentage of the standard loan rate for loan request *i*, CREDRSK_MGR_i is an indicator variable equal to one if the decision rights for loan approval of loan request *i* are delegated to the credit risk manager, zero otherwise, and CRED_COM_i is an indicator variable equal to one if the decision rights for loan approval of loan request *i* are centralized at the credit committee, zero otherwise. Our empirical tests focus on β_1 and β_2. That is, a negative and significant coefficient for β_1 (β_2) suggests that if ratification rights for loan requests are assigned to the credit risk manager (credit committee), those loans are perceived to exhibit more favorable risk-return characteristics, which leads to a downward revision from the standard loan rates for the respective loan requests.

The second dependent variable is whether the Loan Quality Code is downgraded after the loan approval; downgrades are indicative of a change in the risk characteristics of the loan. Note that loan officers do not always limit themselves to communication with an optimistic bias when the loan decision is made, but sometimes also report on the repayment prospects of borrowers with an optimistic bias after the loan decision has been made (Hertzberg et al., 2010). Assuming that the hard, verifiable information does not unambiguously warrant a downgrade, optimistically biased communication of non-verifiable information after the loan approval may bias against finding downgrades. We regress the likelihood of LQC downgrades on the internal decision structure:

$$\text{LQC\_ADAPT}_i = \delta_0 + \delta_1 \ \text{CREDRSK\_MGR}_i + \delta_2 \ \text{CRED\_COM}_i + \text{CONTROLS}_i + \varepsilon_i, \quad (2)$$

where LQC_ADAPT_i denotes an indicator variable equal to one if there is a downgrade in the LQC in a one-year period subsequent to the loan approval, zero otherwise. For an alternative specification of LQC_ADAPT, this variable ranges between zero and four, where zero represents no downgrade and four represents the maximum downgrade possible. Our empirical tests focus on δ_1 and δ_2. A positive and significant coefficient for δ_1 (δ_2) implies that if ratification rights for loan requests are assigned to the credit risk manager (credit committee), those loans face a higher likelihood of downward revision in the loan quality in the year following loan approval.

3.3. Measurement of control variables

We include the following variables in the control function. First, prior studies document the benefits associated with relationship lending. Repeated interactions between the borrowing firm and the bank provide an opportunity for loan officers to accumulate proprietary soft information over time.[13] In our study, the variable PRIOR_REL proxies for the length of the relationship and is equal to one if a client firm has a borrowing relationship with the bank in the past, zero otherwise. Second, small client firms differ from large firms in the production of relatively hard, verifiable information. The decision to extend credit to a larger company can be based more heavily on verifiable information, such as the company's income statements, balance sheet, and credit rating (Stein, 2002; Berger et al., 2005). The variable FIRM_SIZE denotes the natural logarithm of the number of employees of a respective client firm. Third, models of spatial price discrimination explain both the availability and pricing of bank loans. Banks located closer to borrowing firms enjoy significantly lower transportation and monitoring costs which translates into more favorable or unfavorable loan terms, contingent on the physical proximity of other competing banks (Petersen and Rajan, 1995).[14] Close proximity of borrowers also facilitates the collection of soft information by loan officers through a high frequency of personal contact and observation over time (Berger et al., 2005; Agarwal and Hauswald, 2010). DIST denotes the geographical distance between the borrowing firm and the bank, measured in kilometers on the basis of the municipality in which the firm and bank are located, and is equal to one if the distance is higher than the median value, zero otherwise.

Fourth, if the bank represents the main banking relationship for the borrowing firm, information retrieved from e.g., transaction accounts can increase the accuracy of the bank's information and reduce monitoring costs (Mester et al., 2007). OUTST_DEBT denotes the natural logarithm of total debt purchased by the borrowing firm at our bank. Fifth, the observable risk of a loan request is associated with standard loan rates such that higher risk implies higher loan rates. However, riskier firms are likely to face a more comprehensive screening process, endowing banks with more soft information on those firms. This soft information will tend to generate deviations from standard loan rates (Cerqueiro et al., 2011). CRED_RISK denotes the comprehensive internal risk assessment of a loan request and is composed of two dimensions: (1) the internal risk rating of the likelihood of default (RISK_SCORE), and (2) the extent to which the debt is collateralized (COLLATERAL). A higher internal rating of the likelihood of default and a lower degree of collateral translate into greater credit risk. We control for year- and quarter effects, as well as for industry effects on borrowing firms (Fama and French, 1997).

4. Empirical results

4.1. Descriptive statistics

Table 3, panel A reports the descriptive statistics for the full sample. First, in a majority of loan requests, the ratification rights for loan approval are delegated to the loan officer. Only in 18% of cases are ratification rights for loan approval assigned to the credit risk manager. Only in 13% of cases are ratification rights centralized with the credit committee. On average, the final loan rate is lower compared to the standard loan rate, with a mean loan rate deviation of -0.84%. The average total outstanding debt is about €400 K, and a borrowing firm has on average 4 employees. Considering that the 374 loan requests originate from 305 firms, this implies that the borrowing firms represent a total amount of outstanding debt for this bank of about €120 million. Borrowing firms are on average classified as moderately risky; the mean credit risk rating is about 7 on a scale that ranges from 1 (low credit risk) to 14 (high credit risk). This credit risk can be further broken down into the internal risk score of the likelihood of default and the loss given default (the inverse of the amount of collateral). The internal risk score has a mean value of 15 on a scale ranging between 0 and 20 while the debt is on average for about 67% secured by collateral. 11% of the loans experience a loan quality downgrade in the year following loan approval. On average, the borrowing firm is located 14 km from the bank's office which facilitates the accumulation of soft information by loan officers through frequent personal contact and observation over time. Also, about 95% of loan requests originate from borrowing firms that had a past relationship with this bank.

[13] Relationship lending increases the availability of credit (Petersen and Rajan, 1994; Agarwal and Hauswald, 2010), lower loan rates (Berger and Udell, 1995), and lowers collateral requirements (Berger and Udell, 1995). An alternative view is that the borrower may be 'locked-in'. This lock-in effect is most relevant only for borrowers with few or no alternative sources of financing beyond the relationship bank (Bharath et al., 2011).

[14] Degryse and Ongena (2005) provide an overview of the theories explaining the relationship between e.g., loan rates and the distance between a firm and the lending bank, and the distance between a firm and competing banks.

Table 3
Descriptive statistics.

Panel A: Descriptive statistics (full sample)

Variable	Mean	Std. Dev.	10%	25%	50%	75%	90%
RATE_DEV	−0.84	0.96	−2.23	−1.41	−0.71	−0.06	0.20
CREDRSK_MGR	0.18	0.38	0.00	0.00	0.00	0.00	1.00
CRED_COM	0.13	0.34	0.00	0.00	0.00	0.00	1.00
OUTST_DEBT	12.90	1.54	10.82	12.07	13.01	13.84	14.82
CRED_RISK	6.79	3.40	2.00	4.00	7.00	9.00	11.00
RISK_SCORE	15.39	2.50	13.00	14.00	15.00	17.00	18.00
COLLATERAL	67.24	32.89	3.04	49.87	76.05	97.48	99.26
LQC_ADAPT	0.11	0.32	0.00	0.00	0.00	0.00	1.00
SIZE	1.36	1.43	0.00	0.69	0.69	2.07	2.77
DIST	13.52	18.65	3.00	3.00	7.00	17.00	27.00
PRIOR_REL	0.95	0.21	1.00	1.00	1.00	1.00	1.00
Y2008	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Q1	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Q2	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Q3	0.20	0.40	0.00	0.00	0.00	1.00	1.00
Q4	0.18	0.38	0.00	0.00	0.00	1.00	1.00

Panel B: Descriptive statistics (by HIGHER_LEVEL)

Variable	HIGHER_LEVEL = 0			HIGHER_LEVEL = 1			Difference tests		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	St. Dev
RATE_DEV	−0.76	−0.60	0.93	−1.01	−0.97	1.00	**	***	
OUTST_DEBT	12.36	12.55	1.22	14.10	14.13	1.49	***	***	***
CRED_RISK	6.88	7.00	3.37	6.57	7.00	3.47			
RISK_SCORE	15.59	15.00	1.95	14.97	15.50	3.39	**	***	***
COLLATERAL	68.06	77.80	32.99	65.42	74.17	32.74			
LQC_ADAPT	0.06	0.00	0.24	0.22	0.00	0.42	***	***	***
SIZE	1.23	0.69	0.97	1.66	0.69	2.11	***	***	***
DIST	14.30	7.00	19.55	11.78	6.50	16.43			**
PRIOR_REL	0.95	1.00	0.23	0.97	1.00	0.16			***

Panel C: Sample composition over loan officers for the full sample and by authority level

	Age	Tenure	Full sample	Level 1	Level 2	Level 3
Loan officer_1	39	11	28 (7%)	3 (1%)	6 (9%)	19 (39%)
Loan officer_2	34	10	15 (4%)	4 (2%)	6 (9%)	5 (10%)
Loan officer_3	33	7	53 (14%)	38 (15%)	11 (16%)	4 (8%)
Loan officer_4	38	10	68 (18%)	58 (22%)	8 (12%)	2 (4%)
Loan Officer_5	38	7	52 (14%)	42 (16%)	10 (15%)	0 (0%)
Loan officer_6	33	1	37 (10%)	35 (14%)	1 (2%)	1 (2%)
Loan officer_7	57	21	50 (13%)	31 (12%)	11 (16%)	8 (16%)
Loan officer_8	41	8	51 (14%)	42 (16%)	6 (9%)	3 (6%)
Loan officer_9	40	12	20 (5%)	5 (2%)	8 (12%)	7 (14%)
Total			374 (100%)	258 (100%)	67 (100%)	49 (100%)

Panel D: Sample composition over industries.

Industry	Frequency
Agriculture	7 (2%)
Food products	9 (2%)
Entertainment	8 (2%)
Printing and publishing	5 (1%)
Consumer goods	3 (1%)
Healthcare	24 (6%)
Chemicals	2 (1%)
Construction	25 (7%)
Fabricated products	3 (1%)
Machinery	3 (1%)
Miscellaneous	3 (1%)
Personal services	38 (10%)
Business services	69 (18%)
Transportation	7 (2%)
Wholesale	27 (7%)
Retail	38 (10%)
Restaurant, hotels, and motels	22 (6%)
Insurance	5 (1%)

(*continued on next page*)

Table 3 (*continued*)

Panel D: Sample composition over industries.

Industry	Frequency
Real estate	30 (8%)
Trading	47 (13%)
Total	374 (100%)

Variable definitions: RATE_DEV is the actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request, CREDRSK_MGR is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager, zero otherwise, CRED_COM is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit committee, zero otherwise, HIGHER_LEVEL is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager or the credit committee, zero otherwise, OUTST_DEBT is the natural logarithm of total debt borrowed by the firm at the respective bank, CRED_RISK is the internal credit risk assessment of a loan request which captures the likelihood of default and the loss given default, RISK_SCORE is an internal risk assessment of likelihood of default for loan request, COLLATERAL is an internal bank assessment of the degree in which the debt is secured by collateral, indicative of the loss given default for a loan request, LQC_ADAPT is an indicator variable equal to one if the loan experienced a loan quality downgrade in the year following loan approval, zero otherwise, SIZE is the natural logarithm of number of employees of a borrowing firm, DIST is an indicator variable equal to one if the geographical distance between the bank and the borrowing firm is higher than the median value, zero otherwise, PRIOR_REL is an indicator variable equal to one if a client firm has a past borrowing relationship with the bank, zero otherwise, Y2008 is an indicator variable equal to one if the loan request is approved in the year 2008, zero otherwise, Q1 is an indicator variable equal to one if the loan request is approved in the first quarter, zero otherwise Q2 is an indicator variable equal to one if the loan request is approved in the second quarter, zero otherwise, Q3 is an indicator variable equal to one if the loan request is approved in the third quarter, zero otherwise, and Q4 is an indicator variable equal to one if the loan request is approved in the fourth quarter, zero otherwise.

In panel B of Table 3, we report the descriptive statistics for the subsamples in which loan officers decide on the loan (HIGHER_LEVEL = 0) versus those in which higher-level decisions are taken on the loan (HIGHER_LEVEL = 1). We can infer from tests for significance of differences in means and medians that the discounts on standard loan rates are greater in the case of higher-level decision making relative to cases where loan officers are assigned decision rights. However, a test for the equality of variances across subsamples does not indicate differences in the dispersion of loan rate deviations across subsamples. Furthermore, loans that require higher-level decision making are, on average, characterized by greater outstanding debt but not greater credit risk. Note that it is the combination of outstanding debt and credit risk that determines where loans are decided on, such that smaller (greater) loans with both moderate credit risk are assigned to loan officers (higher-level officers) for approval. If we look at the internal risk rating (RISK_SCORE), we can see that loans decided on by loan officers are characterized by a higher risk score, but that on the other hand the dispersion in the risk score is greater for loans that require approval from higher-level officers. Finally, we see that loans to larger firms are more often decided on by higher-level officers and that loans whose decision rights are assigned to higher-level officers more often face downgrades after the loan has been granted.

Panel C of Table 3 reports the age and tenure of loan officers at this bank. On average, loan officers serve as account managers for their client firms for about 10 years. This implies that the loan officers are in a position to accumulate soft information on their client firms over the course of years.[15] Additionally, panel C shows the composition of the sample of loan files over different loan officers. It clearly shows some difference between loan officers in terms of the number of loan files that each loan officer manages. In addition, panel C reports the distribution of loan requests over the distinguished authority levels for each loan officer. It seems that some loan officers differ to the extent by which decision rights for loans are assigned to them or to higher-level decision makers. Ratification rights seem to be more often delegated to busy loan officers (officers that manage a great number of loan requests) relative to loan officers that manage a smaller number of loans. It is possible that some loan officers handle a smaller number of more complex loan files that require higher authority levels for decision-making. Another possibility is that reputational effects of loan officers come into play. In our analyses we include loan officer fixed effects, given the focal role of loan officers in the accumulation of soft information about prospective borrowing firms.[16]

Table 3, panel D reports the composition of the sample over different industries as defined by Fama and French (1997). The sample has a strong representation in Personal Services (10%), Business Services (18%), and Trading (13%).

4.2. Empirical tests of internal bank procedures

In this section we empirically verify internal procedures at our sample bank. We conduct this analysis to examine whether the credit risk rating and total outstanding debt are, as suggested by internal bank procedures, the main determinants of the assignment of loans to different hierarchical levels. We first examine how credit risk ratings are determined as these ratings are an important input for the standard loan rate. We run a regression of the credit risk rating (which varies between 1 and 14) on an internal risk score which proxies for the probability of default (RISK_SCORE) and the degree to which the debt is secured by collateral which represents the inverse of the loss given default (COLLATERAL). We include loan officer and industry fixed effects.

[15] Only one loan officer at our sample bank is relatively new, with a tenure of about one year. As short-tenured loan officers will have collected less knowledge of their clients, they have less information they can use to plead for discounts on standard loan rates compared to their more experienced colleagues. A t-test for differences in means indeed shows that this officer has significantly more positive loan rate deviations, while controlling for outstanding debt and credit risk (not tabulated).

[16] For example, more reputable loan officers may be more likely to take on loan files characterized by higher credit risk ratings and/or greater total debt (more likely to be assigned to a higher-level officer) and those officers may on the basis of their reputations be more likely to attain favorable loan conditions (lower loan rates).

Table 4
Empirical tests of internal bank procedures.

Dependent variable		CRED_RISK	HIERARCHY
Intercept		0.82 (0.72)	–
RISK_SCORE	+	0.74^{***} (17.07)	–
COLLATERAL	+	-0.08^{***} (-26.55)	–
CRED_RISK	+	–	0.17^{***} (3.73)
OUTST_DEBT	+	–	1.32^{***} (5.04)
Industry effects		Yes	Yes
Loan officer effects		Yes	Yes
Number of obs.		374	374
(pseudo) R^2		0.66	0.41
Model significance		$F = 36.07^{***}$	Wald $\chi^2 = 3808.10^{***}$

In the left column we explain the computation of the credit risk rating for a loan request by means of the internal risk score (the likelihood of default) and the degree to which the debt is secured by collateral (the inverse of the loss given default). In the right column we explain the assignment of loan requests over different hierarchical levels by means of the credit risk rating and the outstanding debt. This is described by the following two models:
$CRED\_RISK_i = \alpha_0 + \alpha_1 RISK\_SCORE + \alpha_2 COLLATERAL + \varepsilon_i$ (1).
$HIERARCHY_i = \gamma_0 + \gamma_1 CRED\_RISK_i + \gamma_2 OUTST\_DEBT_i + \varepsilon_i$ (2).
The first model is estimated by robust regression and the second model is estimated by ordered logistic regression with clustered standard errors. The t-statistics are reported in parentheses. Industry effects are based on Fama and French (1997) industry classification. ***, **, *, † corresponds to 1%, 5%, 10%, and 15% significance levels (one-tailed when coefficient sign is predicted, two-tailed otherwise).
Variable definitions: CRED_RISK is the internal credit risk assessment of a loan request which captures the likelihood of default and the loss given default, RISK_SCORE is an internal risk assessment of likelihood of default for a loan request, COLLATERAL is an internal bank assessment of the degree in which the debt is secured by collateral, indicative of the loss given default for a loan request, HIERARCHYis equal to one if decision rights for loan approval of a loan request are delegated to the loan officer, equal to two if the decision rights for loan approval are assigned to the credit risk manager, and equal to three if the decision rights are assigned to the credit committee, and OUTST_DEBT is the natural logarithm of total debt borrowed by the firm at the respective bank.

The findings are reported in the left column of Table 4. We employ robust regressions that exclude observations with Cook's D > 1 and then perform Huber iterations followed by biweight iterations. The coefficient on RISK_SCORE is positively and the coefficient on COLLATERAL negatively associated with CRED_RISK ($p < 0.01$). Ordered logistic regression models with clustered standard errors that account for heteroskedasticity and autocorrelation yield similar results.[17] Therefore, the internal credit risk rating is positively associated with the internal assessment of the likelihood of default and negatively associated with the degree that the loan is secured with collateral.

Second, we examine the delegation of decision rights within the bank. We distinguish between three different levels. Hierarchy is a variable equal to one if ratification rights for loan approval are delegated to the loan officers, equal to two if ratification rights for loan approval are assigned to a credit risk manager, and equal to three if ratification rights are assigned to the credit committee (see Table 2). We employ an ordered logistic regression with clustered standard errors that account for both heteroskedasticity and autocorrelation. We regress the variable hierarchy on the credit risk rating (CRED_RISK) and total outstanding debt (OUTST_DEBT). We include loan officer and industry fixed effects. The results are reported in the right column of Table 4. The coefficients for CRED_RISK and OUTST_DEBT are both positive and highly significant ($p < 0.01$). We also find that some loan officer indicators are negative and significant (evaluated at the 10% significance level).[18] This may imply reputational effects if the delegation of decision rights is also influenced by the reputation of loan officers. As a subsequent analysis, we run a logistic regression in which the dependent variable is the variable CRED_COM (non-tabulated). This variable is equal to one if decision rights are assigned to the credit committee (the third level in Table 2) and zero if the decision rights are delegated towards loan officers or the credit risk manager (the first two levels in Table 2). The coefficients on CRED_RISK and total debt are again positive and significant ($p < 0.01$). Now, all loan officer indicators are not significant. This suggests that loan officers have little influence on the ultimate decision of whether the loan approval is made by the credit committee or by a lower-level entity. Nonetheless, we include loan officer fixed effects in our empirical analyses.

In sum, the results corroborate internal bank procedures. The internal risk assessment of the likelihood of default and the amount of collateral predict the comprehensive internal credit risk rating. Furthermore, the internal credit risk rating and the total outstanding debt are associated with the required hierarchical level for loan approval.

4.3. Main analyses

We examine whether loan outcomes differ contingent on whether loan officers or a higher-level entity decide on the loan. We focus on two loan outcomes: (1) deviations from the standard loan rate, and (2) loan quality downgrades in a one-year period following loan approval. The left column of Table 5 reports the regression estimates of robust regressions with, as dependent variable, deviations from the standard loan rate. The results show that higher-level decision making is associated with greater discounts on standard loan rates (lower loan rates). Specifically, the coefficients on CREDRSK_MGR and CRED_COM are both negative and significant ($p < 0.01$). This implies that when decision rights for loan approval are not delegated to loan officers but instead are allocated to credit risk managers or the credit committee, loan officers attain greater discounts on the standard loan rate. This is consistent with our intuition that loan officers make use of soft information in order to communicate optimistically about the risk-return characteristics of the loan request, which in turn facilitates lower loan rates. With regard to the control variables, and consistent with prior research, we show that a higher credit risk is associated with lower loan rates. Loans characterized by greater credit risk face supplemental analysis including both verifiable (e.g., longer history of financial data) and non-verifiable information. Cerqueiro et al. (2011) document how riskier firms face a more intensive screening process, thereby providing banks with more soft information on these firms and explaining adjustments to standard loan rates. In addition, larger firms and firms with greater outstanding debt are associated with premiums on the standard loan rate (higher loan rates).

The right column of Table 5 reports the regression outcomes of a logistic regression, with the likelihood of a loan quality revision as the dependent variable. Recall that loan officers can present a loan application with an optimistic bias to attain lower loan rates which in turn leads to information that reflects the underlying economic fundamentals less well at the time of the loan approval. We use the loan quality code as a proxy for the financial health of the client firm. We collected information on the Loan Quality Codes both at the time of loan approval and one year after the loans had been approved. Note that at the time of loan approval, all our loan proposals were equal to the level of "Continuity." One year after approval, 332 loans had the code "Continuity", 27 loans had the code "Attention-seeking", 12 loans had the code "Vulnerable Continuity", and 3 loans had the code

[17] Standard errors of loan files from the same firm may not be independent as residuals can be correlated across time (time-series dependence) for a given firm. Clustered standard errors are unbiased as they account for residual dependence created by a panel data structure and account for general forms of heteroskedasticity (Petersen, 2009).

[18] More specifically, four out of nine loan officers report negative and significant coefficients evaluated at the 10% significance level (not tabulated).

Table 5
Delegation of decision rights and loan outcomes.

Dependent variable	Prediction	RATE_DEV	LQC_ADAPT
Intercept		−1.29** (-2.05)	−13.44*** (-3.53)
CREDRSK_MGR	?	−0.30*** (-2.79)	0.58 (0.98)
CRED_COM	?	−0.54*** (-3.64)	1.74** (2.19)
OUTST_DEBT		0.11*** (3.19)	0.48** (1.97)
RISK_SCORE		−0.12*** (-7.05)	0.29*** (3.36)
COLLATERAL		0.02*** (13.96)	−0.01 (−0.69)
SIZE		0.09** (2.83)	0.21 (1.26)
DIST		−0.00 (-0.45)	−0.00 (-0.25)
PRIOR_REL		−0.20 (-1.09)	−0.36 (-0.24)
Y2008		0.06 (0.59)	0.45 (0.91)
Quarter effects		Yes	Yes
Loan officer effects		Yes	Yes
Industry effects		Yes	Yes
Number of obs.		374	374
(pseudo) R^2		0.42	0.26
Model significance		$F = 12.26$***	$\chi^2 = 59.12$***

This table reports the regression estimates of robust regressions explaining two loan outcomes: (1) deviations from standard loan rates, and (2) loan quality downgrades following loan approval. This is described by the following two models:

$RATE\_DEV_i = \beta_0 + \beta_1\ CREDRSK\_MGR_i + \beta_2\ CRED\_COM_i + CONTROLS_i + \varepsilon_i$ (1).

$LQC\_ADAPT_i = \delta_0 + \delta_1\ CREDRSK\_MGR_i + \delta_2\ CRED\_COM_i + CONTROLS_i + \varepsilon_i$ (2).

The first model is estimated by robust regression and the second model is estimated by logistic regression with clustered standard errors. The t-statistics are reported in parentheses. Industry effects are based on Fama and French (1997) industry classification. ***, **, *, † corresponds to 1%, 5%, 10%, and 15% significance levels (one-tailed when coefficient sign is predicted, two-tailed otherwise).

Variable definitions: RATE_DEV is the actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request, LQC_ADAPT is an indicator variable equal to one if there is a downgrade in Loan Quality Code in a one-year period following loan approval, zero otherwise, CREDRSK_MGR is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager, zero otherwise, CRED_COM is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit committee, zero otherwise, OUTST_DEBT is the natural logarithm of total debt borrowed by the firm at the respective bank, RISK_SCORE is an internal risk assessment of the likelihood of default for a loan request, COLLATERAL is an internal bank assessment of the degree to which the debt is secured by collateral, indicative of the loss given default for a loan request, SIZE is the natural logarithm of number of employees of a borrowing firm, DIST is an indicator variable equal to one if the geographical distance between the bank and the borrowing firm is higher than the median value, zero otherwise, PRIOR_REL is an indicator variable equal to one if a client firm has a past borrowing relationship with the bank, zero otherwise, Y2008 is an indicator variable equal to one if the loan request is approved in the year 2008, zero otherwise.

“Emerging Discontinuity”. LQC_ADAPT is an indicator variable equal to one if the respective loan quality code is downgraded, zero otherwise.

The evidence does not suggest that loans approved by the credit risk manager face an increased likelihood of loan quality downgrade the year after the initial approval. The coefficient on CREDRSK_MGR is not significant. However, we find that loans approved by the credit committee, while controlling for the risk score and outstanding debt, are associated with downgrades in the loan quality codes. That is, the coefficient on CRED_COM is positive and significant ($p < 0.05$). These results suggest that when ratification rights are assigned to the credit committee, loan officers favorably assess the risk-return characteristics of the loan application to the extent that these loans are more likely to face a loan quality downgrade after approval. With regard to the control variables, we find that loans characterized by higher risk scores ($p < 0.01$) and greater amounts of total debt ($p < 0.05$) feature an increased likelihood of a downgrade in the Loan Quality Code after the initial loan approval. We include quarter effects, loan officer effects, and industry effects in both models.[19]

4.3.1. Supplemental analyses

We perform a range of supplemental non-tabulated analyses. First, in the analyses reported in Table 5, we control for credit risk and outstanding debt in a linear manner. Given that our outcome variables can be related to debt and credit risk in a nonlinear fashion, we repeat the analyses while replacing the control variables credit risk and outstanding debt with several indicator variables to allow for nonlinear effects. We replace RISK_SCORE with five indicator variables equal to one if the RISK_SCORE is 11 or12, zero otherwise; equal to one if the RISK_SCORE is 13 or 14, zero otherwise; and so on, up to the point that the final variable is equal to one if RISK_SCORE is 19 or 20, zero otherwise. We replace COLLATERAL with four indicator variables on the basis of quintiles. We replace OUTST_DEBT with nine indicator variables equal to one if the size of debt ranges between €25 K and €50 K, zero otherwise; equal to one if OUTST_DEBT ranges between €50 K and €100 K, zero otherwise; up to the point that the final indicator variable is equal to one if OUTST_DEBT is greater than €5000 K, zero otherwise. That is, we use the same total debt classification as used by our sample bank (reported in Table 1), with the only difference being that we aggregate the final three debt categories into one single indicator variable. Our main inferences are not affected by controlling for credit risk and debt in a nonlinear fashion. That is, while controlling for quarter and industry effects, both coefficients on D_CREDRISK and D_CREDCOM are negative and significant ($p < 0.01$, two-tailed) in explaining loan rate deviations. For the loan quality downgrades, the coefficient on D_CREDCOM is positive and significant ($p < 0.01$, two-tailed).

Second, we allow for the possibility that the standard loan rate table (see Table 1) is miscalibrated such that, e.g., loan files that must be forwarded to higher level officers have less favorable standard loan rates than strictly necessary. If this is the case, the greater downward deviations from standard loan rates for loans that require approval from higher-level officers are a mechanical artifact that follows from the miscalibration of the standard loan rate table. While we do not have the actual loan rates, we can model the actual loan rates for each loan by estimating the base rate as a constant of 2%, add the actual mark-up that is applied by our sample bank on the basis of credit risk and outstanding debt, and subtract (if a discount is awarded from the standard loan rate) or add (if a premium is applicable) the deviation from the standard loan rate. We repeat the analyses reported in the left column of Table 5, but now with the loan rate as the dependent variable. Our inferences are not affected. That is, the coefficients on D_CREDRISK and D_CREDCOM are negative and significant (D_CREDRISK = -0.29, $p = 0.02$, two-tailed; D_CREDCOM = -0.39, $p = 0.03$, two-tailed). With respect to the control variables, we find that loan rates are decreasing in total outstanding debt and the degree in which loans are secured with collateral, and loan rates are increasing in the bank's internal risk assessment of the likelihood of default (RISK_SCORE).

Third, to substantiate our prior findings on loan rate deviations, we employ a regression discontinuity design. That is, we examine a subset of loan files that are just below and just above the threshold that identifies which loan files may be approved by the loan officers themselves and which loan files must be approved by higher-level decision makers. In effect, we examine what the effect is of the

[19] We repeat the analysis explaining loan quality revisions, but now define LQC_ADAPT as an integer between zero and four, where zero denotes no downgrade in the loan quality code, one denotes a downgrade from ‘Continuity’ towards ‘Attention-seeking,’ and so on, until four, which denotes a downgrade from ‘Continuity’ towards ‘Discontinuity.’ Our findings remain unchanged. A Tobit regression shows that the coefficient on CREDRSK_MGR is insignificant and the coefficient on CRED_COM is positive and significant (p = 0.01).

hierarchical decision level for loans that are similar in credit risk and size of debt. Our treatment variable (HIGHER_LEVEL) is an indicator variable equal to one for loans assigned to the credit risk manager or credit committee for ratification, and equal to zero when loan officers are authorized to decide on the loans. We compare loans that are relatively similar in the assignment variables (CRED_RISK and OUTST_DEBT) with the only difference being that on the basis of the respective thresholds some loans are just below the threshold and therefore may be approved by the loan officer themselves, while other loans just exceed the threshold and must be approved by higher-level officers.[20] We use the following procedure. Given that there are different debt thresholds for separate risk categories (e.g., a debt threshold of €800,000 for loans featuring a credit risk between 1 and 3; see Table 2), we compute for each loan on the basis of the respective credit risk categories a distance measure that conveys whether the debt (OUTST_DEBT) of a loan is below or above the debt threshold for the corresponding credit risk category and how far it is removed from the threshold. We examine the outcome variable (deviation from standard loan rates)[21] in the neighborhood of the discontinuity. To decrease the likelihood that our inferences regarding the treatment effect are affected by the functional form of the relationship at both sides of the discontinuity, we examine the outcome variable of interest in a small neighborhood around the discontinuity. We obtain about 30 observations on both sides of the discontinuity.[22] The mean deviation from the standard loan rate is more negative when loan files must be approved by higher-level officers compared to when loan files can be approved by loan officers themselves ($p < 0.05$, one-tailed). We employ a local linear regression in which deviations from the standard loan rate are regressed on the distance from the threshold, using a rectangular kernel.[23] The coefficient that denotes the treatment effect when loan proposals are assigned to higher-levels for ratification is negative and significant ($p < 0.07$, one-tailed). We employ different bandwidths that result in subsamples ranging from about 20 observations to 40 observations on each side of the discontinuity (Imbens and Lemieux, 2008). Our inferences are not affected.

4.3.2. Does audited information moderate relations between higher-level decisions and loan discounts?

Our intent is to provide evidence for the mechanism underlying our findings. We believe that the soft information collected by loan officers enables them to present the risk-return characteristics of the loan files in an optimistic way given that small firms have a limited supply of hard, verifiable information. However, a greater supply of hard, verifiable information may decrease the weight assigned to soft information in loan decisions. Minnis (2011) shows how audited accounting reports lead to more intensive use of accounting information by banks in making loan pricing decisions compared to unaudited reports. In our setting, one of the determining factors that require private firms to have mandatory auditing is whether they have more or less than 50 employees.[24] We define an indicator variable AUDIT that is one if a client firm has 50 or more employees, zero otherwise. We interact the variable AUDIT with the variable HIGHER_LEVEL equal to one for loans assigned to the credit risk manager or credit committee for ratification, and equal to zero when loan officers are authorized to decide on the loans. Table 6 reports our results.[25] The coefficient on HIGHER_LEVEL denotes the relation between higher level lending decisions and loan rate deviations for unaudited client firms. This coefficient is negative and significant ($p < 0.01$, two-tailed). The coefficient on HIGHER_LEVEL*AUDIT reflects the difference in the relation between higher-level loan decisions and loan rate deviations for unaudited vs. audit client firms. This coefficient is positive and significant ($p = 0.07$, two-tailed). The sum of coefficients (HIGHER_LEVEL + HIGHER_LEVEL*AUDIT) indicative of the relation between higher level lending decisions for audited client firms and loan rate deviations is not significant. The results suggest that higher level decision making only leads to discounts on standard loan rates for firms that do not have audited financial statements. This is consistent with the intuition that for audited firms, lending decisions are more based on hard, verifiable information which limits the role of loan officers in presenting their soft information with an optimistic bias.

4.4. Robustness analyses

4.4.1. Sample of approved loan proposals

Our sample consists of approved loan requests. At our sample bank, denial of loan applications occurs infrequently as our sample bank represents the main banking relationship for many SMEs and therefore access to capital primarily depends on loan decisions made by the bank. Loan officers play an important role; they have a thorough understanding of business needs and guide business owners in structuring loan applications (e.g., loan amount, collateral) in order to increase the likelihood of a favorable loan-decision outcome. Anecdotal evidence on the small number of loan denials coincides with research that suggests that banks that engage in relationship lending accumulate valuable information on the inherent quality of lenders and tolerate temporarily bad results (while changing the terms of the loan) as long as they can secure long-term rents (Schäfer, 2016).

Next, we examine whether loan denials differ in frequency across hierarchical levels since, for example, loan files that are riskier face a greater likelihood of being assigned to higher-level officers for approval on the one hand, and stand a greater chance of being rejected on the other. Loan denials that are concentrated at the credit committee level may lead to approved loan proposals that feature a truncated distribution with a high proportion of negative loan rate deviations (discounts on standard loan rates) and a small proportion of positive loan rate deviations (premiums), which may represent an alternative explanation for one of our two main findings (the negative coefficient on D_CREDCOM in the model explaining loan rate deviations). First, while we do not have data on denial for individual loan files, we were able to retrieve aggregate data on loan approval rates for different decision levels. Loan approval rates are similar across different decision levels. Second, as this alternative explanation implies that the distribution of

[20] We exploit the fact that treatment (HIGHER_LEVEL) is a discontinuous function of the assignment variables, given that no matter how close the value of OUTST_DEBT gets to the threshold, treatment is administered if the value of OUTST_DEBT meets or exceeds the threshold.

[21] We define our outcome variable as follows: Given the variation in CRED_RISK within the debt categories (e.g., a debt category of €250K-€600Kcontains loans that feature credit risk ratings between 9 and 14), and we observe significant differences in credit risk rating across both sides of the discontinuity, we regress our outcome variable on the credit risk ratings (while we allow for nonlinearities) and use the residual as our outcome variable of interest.

[22] Given that observations are more dispersed on the right side of the discontinuity, we employ a greater bandwidth to get approximately equally-sized portfolios on each side of the discontinuity.

[23] That is, greater weight is accorded to observations closer to the discontinuity.

[24] Two other requirements are based on the values of net sales and the total balance sheet where financial reports have to be audited when two out of three requirements are satisfied for two consecutive years. Our proxy has some measurement error as it does not directly measure whether financial statements are audited. Firms that meet this criterion may not meet one of the other two criteria and firms may voluntarily choose to audit their reports. Given that firms qualify when they meet two out of the three criteria and that the criteria are most likely to be positively correlated, we believe that the variable AUDIT is a reasonable proxy for audited financial reports.

[25] In our analyses, we include controls as well as quarter and industry effects. Given that the variable AUDIT is based on the number of employees, we remove size from our control function.

Table 6
Does audited information moderate the relation between higher-level decisions and loan rate discounts?

Dependent variable	Prediction	RATE_DEV
HIGHER_LEVEL	?	-0.44^{***} (-4.37)
HIGHER_LEVEL*AUDIT	?	0.36^{*} (1.79)
F-test ($\delta_1 + \delta_2 = 0$)		0.12
Controls		Yes
Quarter / industry effects		Yes
Number of obs.		374
Model significance		$F = 14.13^{***}$

This table reports the regression estimates of robust regressions explaining how the relation between higher-level decision making and deviations from standard loan rates differs contingent on the supply of audited information. This is described by the following model:

$RATE\_DEV_i = \delta_0 + \delta_1\ HIGHER\_LEVEL_i + \delta_2\ HIGHER\_LEVEL_i{*}AUDIT_i + CONTROLS_i + \varepsilon_i$ (1).

The model is estimated by robust regression. The t-statistics are reported in parentheses. Industry effects are based on Fama and French (1997) industry classification. ***, **, *, † corresponds to 1%, 5%, 10%, and 15% significance levels (one-tailed when coefficient sign is predicted, two-tailed otherwise).

Variable definitions: RATE_DEV is the actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request, HIGHER_LEVEL is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager or the credit committee, zero otherwise, AUDIT is an indicator variable equal to one if the respective borrower has 50 or more employees as this is one of the criteria for mandatory auditing, zero otherwise.

loan rate deviations is truncated at a credit committee level, we tested whether the variance of loan rate deviations was smaller at the credit committee level, relative to the loan officer decision-level (not tabulated). The F-test for equality of variances rejects the null that the variance of loan rate deviations is significantly different between the two decision levels ($p = 0.94$, two-tailed). The test statistic of Levene (1960), robust under nonnormality, also rejects the null-hypothesis of significant differences in the variances ($p = 0.89$). The results remain unchanged when alternative measures of centrality are used such as the median. In sum, loan denial is infrequent in our setting and we find no evidence of higher loan denial rates at the credit committee level.

4.4.2. The effect of centralization on loan officers' incentives to collect information

Loan officers who do not have formal authority in terms of loan approval face the possibility that their proposals will be overruled by the credit committee. This possibility may affect the incentive for loan officers to collect information. When loan officers collect lower quality information, this in turn can affect loan decisions when formal authority lies with a higher-level entity. Lower quality information can be an alternative explanation for the increased likelihood of loan quality downgrade when loans must be approved by higher-level officers. As a robustness analysis, we examine whether the internal risk score may be perceived as being of lower quality when the loan approval authority is not assigned to the loan officer, but instead to a higher level. We regress the loan quality downgrades on, amongst others, the risk score (RISK_SCORE), while interacting the risk score with an indicator variable (HIGHER_LEVEL) equal to one if the authority for loan approval is assigned to the credit risk manager or credit committee, zero otherwise:

$$LQC\_ADAPT_i = \theta_0 + \theta_1 HIGHER\_LEVEL_i + \theta_2 RISK\_SCORE_i + \theta_3 HIGHER\_LEVEL{*}RISK\_SCORE + CONTROLS_i + \varepsilon_i \quad (3)$$

The coefficient on RISK_SCORE reflects the association between the risk score and loan quality downgrades for loans approved by loan officers. The sum of coefficients (RISK_SCORE + RISK_SCORE *HIGHER_LEVEL) represents the association between the internal risk score and the loan quality downgrade for loans pushed up in the hierarchy for approval. The coefficient on RISK_SCORE*HIGHER_LEVEL reflects the difference in the relation between the risk score and loan quality downgrades for loans to be approved by loan officers vis-à-vis a higher-level entity. The results of a logistic regression do not suggest that the internal risk score contains less information for predicting future loan quality downgrades when the authority for loan approval is assigned to a higher-level entity (non-tabulated). Specifically, the coefficient on RISK_SCORE is positive and significant (coefficient = 0.34, $p = 0.01$, two-tailed), while the coefficient on RISK_SCORE*HIGHER_LEVEL is not significant (coefficient = -0.06, $p = 0.70$). Besides defining LQC_ADAPT as an indicator variable, we also define LQC_ADAPT as an integer between zero and four, where zero represents no downgrade and four represents the maximum downgrade in Loan Quality Code. A Tobit regression yields similar findings. The coefficient on RISK_SCORE is positive and significant (coefficient = 0.34, $p < 0.01$, two-tailed), while RISK_SCORE*HIGHER_LEVEL is insignificant (coefficient = -0.01, $p = 0.95$). Both models include controls, quarter effects, loan officer effects, and industry effects. In sum, the evidence suggests that lower quality information due to decreased incentives for loan officers to collect information when formal authority is assigned to a higher decision-level does not provide an alternative explanation for our findings.

4.4.3. The effect of higher-level screening on the quality of approved loan requests

An organizational structure in which the loan officer reviews a loan request and subsequently seeks approval from a higher-level entity (credit committee) may have an effect on loan decisions. Sah and Stiglitz (1986) argue that a hierarchy in which there is sequential decision making of a lower-level unit and higher-level unit reduces the likelihood of loan approval but may increase the quality of approved loans.[26] This may provide an alternative explanation for one of our findings as increased loan quality may translate into greater downward deviations from standard loan rates. It is less clear how increased loan quality explains a greater likelihood of future loan quality downgrades.

As a robustness check, we use four proxies for the quality of decision making at the credit committee level to verify whether higher quality decision-making at the credit committee level influences loan rate deviations and/or loan quality reclassifications. First, we look at the number of loan requests to be discussed in a credit committee meeting where we expect that a low number of loan requests indicates a higher quality of decision making. We use an indicator variable (LOW_#LOANS) equal to one if one loan request is to be discussed, zero otherwise. Second, we look at the number of higher-level officers who attend the meeting where we expect that quality increases in the number of officers. We use an indicator variable (HIGH_CCSIZE) equal to one if five officers attend the meeting, zero otherwise. Third, we look at the average tenure of the attending officers at the bank which proxies for the bank-specific experience of higher-level officers. We use an indicator variable (HIGH_TENURE) equal to one if the average tenure is equal to or higher than 14 years, zero otherwise. Fourth, we look at the average age of the attending officers which proxies for the overall experience of the officers. We use an indicator variable (HIGH_AGE) equal to one if the average age is equal to or higher than 45 years, zero otherwise.[27] The interaction terms between CREDCOM and the proxies

[26] Sah and Stiglitz (1986) compare polyarchies (where decision-making is parallel) with hierarchies (where decision-making is sequential). Assuming that decision making (screening) is neither completely flawless nor erroneous, the two systems aggregate errors differently. The proportion of accepted projects is smaller in hierarchies compared to polyarchies. Hierarchies accept a smaller fraction of bad projects (that should have been rejected) and reject a larger fraction of good projects (that should have been accepted).

[27] The number of loans discussed in a credit committee meeting ranges between one and three, the number of higher-level officers ranges between three to five, the average tenure ranges between 8 and 18 years, and the average age

Table 7
The effect of higher-level screening on the quality of approved loan requests.

Dependent variable	Prediction	RATE_DEV		LQC_ADAPT	
CREDRSK_MGR	?	−0.31*** (-2.87)	−0.30*** (-2.77)	0.47 (0.78)	0.58 (0.97)
CRED_COM	?	−0.70*** (-3.46)	−0.47*** (-2.62)	2.49** (2.39)	1.75* (1.69)
CRED_COM*LOW_#LOANS		0.36 (1.42)	–	−3.66*** (-2.94)	–
CRED_COM*HIGH_CSIZE		−0.02 (-0.10)	–	−0.03 (0.97)	–
CRED_COM*HIGH_TENURE		–	0.19 (0.51)	–	−0.02 (-0.02)
CRED_COM*HIGH_AGE		–	−0.46 (-1.24)	–	0.00 (0.00)
Controls		Yes	Yes	Yes	Yes
Quarter/loan officer/industry effects		Yes	Yes	Yes	Yes
Number of obs.		374	374	374	374
Model significance		F = 10.95***	F = 11.47***	χ^2 = 64.24***	χ^2 = 61.21***

This table reports the effect of the quality of screening by the credit committee on the relation between ratification of loan requests at the credit committee on the one hand and deviations from standard loan rates and the likelihood of loan quality revisions on the other. This is described by the following two models:
$RATE\_DEV_i = \lambda_0 + \lambda_1 CREDRSK\_MGR_i + \lambda_2 CRED\_COM_i + \lambda_3 CREDCOM*QUALITY\_PROXY + CONTROLS_i + \varepsilon_i$ (1).
$LQC\_ADAPT_i = \lambda_0 + \lambda_1 CREDRSK\_MGR_i + \lambda_2 CRED\_COM_i + \lambda_3 CREDCOM*QUALITY\_PROXY + CONTROLS_i + \varepsilon_i$ (2).
The first model is estimated by robust regression and the second model is estimated by logistic regression with clustered standard errors. The T-statistics are reported in parentheses. Industry effects are based on Fama and French (1997) industry classification. ***, **, * corresponds to 1%, 5%, and 10% significance levels (two-tailed).
Variable definitions: RATE_DEV is the actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request, LQC_ADAPT is an indicator variable equal to one if there is a downgrade in Loan Quality Code in a one-year period following loan approval, zero otherwise. CREDRSK_MGR is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager, zero otherwise, CRED_COM is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit committee, zero otherwise, LOW_#LOANS is an indicator variable that proxies for the quality of decision-making by the credit committee and is equal to one if one loan file is to be discussed at a credit committee meeting, zero otherwise, HIGH_CCSIZE is an indicator variable that proxies for the quality of decision-making by the credit committee and is equal to one if five officers attend the credit committee meeting, zero otherwise, HIGH_TENURE is an indicator variable that proxies for the quality of decision-making by the credit committee and is equal to one if the branch-specific tenure of members that attend the meeting is higher than or equal to 14 years, zero otherwise, HIGH_AGE is an indicator variable that proxies for the quality of decision-making by the credit committee and is equal to one if the average age (experience) of members that attend a meeting is higher than or equal to 45 years, zero otherwise.

for higher-quality decision-making reflect the extent to which higher quality loans that make it through the credit committee represent an alternative explanation for our findings. The results are reported in Table 7.

The left two columns of Table 7 report the effect of higher quality decision-making on standard loan rate deviations. We do not find any suggestion that improved screening at the credit committee translates into greater downward deviation from standard loan rates. More specifically, none of the four interaction terms is significant. The right two columns of Table 7 report the effect of higher quality decision-making by the credit committee on the likelihood of a loan quality downgrade after loan approval. Again, for three out of our four proxies for the quality of decision making, we do not find evidence that improved screening by the credit committee translates into a lower likelihood of a loan quality downgrade. Only the coefficient on CREDCOM*-LOW_#LOANS is negative and significant. This suggests that a lower number of loans discussed in the credit committee is associated with a smaller likelihood of a future loan quality downgrade. Overall, our findings suggest that a higher quality of loans that are approved by the credit committee does not represent an alternative explanation for our main findings.

4.4.4. Strategic pricing

Credit committees may employ strategic pricing for competitive reasons. For instance, the bank might offer lower loan rates to attract or retain firms. Up to now, we have tried to address strategic pricing as an alternative explanation for our findings by including variables for whether a corporate borrower represents a new client, the amount of total debt purchased by the borrower at our bank, etc. in the control function. We now attempt to further rule out strategic pricing as an alternative explanation by introducing two proxies for the presence of strategic pricing considerations. First, we measure the time between the moment a loan file is put forward to the credit committee and when the credit committee convenes to decide on the loan file. Second, we measure whether the bank provides additional services (treasury services) in addition to the prospective lending agreement.

We propose that strategic pricing considerations are represented by the decision of the credit committee to schedule a meeting shortly after a loan file is put forward by a loan officer to the credit committee for approval.[28],[29] We argue that the time between two credit committee meetings is motivated by: (1) the supply of loan requests and (2) whether or not the application warrants a swift decision in order to make a competitive offer. Therefore, we expect that a short time span between the moment a loan file is forwarded for approval and the credit committee meeting is associated with the presence of strategic pricing considerations for the respective loan. As we have both the dates a loan file is put forward by a loan officer to the credit committee and the dates the credit committee meets, we calculate the number of days that the loan request must wait before being discussed in the credit committee. The average time before a loan file is discussed is six calendar

(*footnote continued*)
of the higher-level officers that attend meetings ranges between 40 and 46 years. Almost all higher-level officers have an MSc. degree so we cannot use educational background as an alternative robustness check.

[28] There is measurement error given that the decision of loan officers when to submit loan files may be influenced by the dates on which committee meetings have been scheduled. Nevertheless, greater importance accorded to loan files also make officers prone to prepare loan files such that they meet the scheduled dates for committee meetings.

[29] We note that during our sample period the credit committee scheduled 27 meetings. The average time between two credit committee meetings is 18 calendar days.

Table 8
The effect of strategic pricing on loan rate deviations and loan quality revisions.

Dependent variable	Prediction	MODEL 1 RATE_DEV	MODEL 1 LQC_ADAPT	MODEL 2 RATE_DEV	MODEL 2 LQC_ADAPT
CREDRISK_MGR	?	−0.31*** (-2.87)	0.59 (1.01)	−0.31*** (-2.74)	0.57 (0.96)
CRED_COM	?	−0.69*** (-3.88)	2.23*** (2.65)	−0.62*** (-4.02)	1.68** (2.05)
CRED_COM*TIME_LOW		0.11 (0.60)	−1.06 (-1.28)	–	–
TREASURY_SERVICES		–	–	−0.08 (-0.54)	0.34 (0.43)
Controls		Yes	Yes	Yes	Yes
Quarter/loan officer/industry effects		Yes	Yes	Yes	Yes
Number of observations		374	374	374	374
Model significance		$F = 11.53^{***}$	$\chi^2 = 68.21^{***}$	$F = 13.26^{***}$	$\chi^2 = 66.11^{***}$

This table reports the effect of strategic pricing on loan outcomes. Model 1 exploits the variation in the time between the moment a loan file is put forward to the credit committee and the moment the credit committee meets as a proxy for the strategic importance of a loan. The model examines the effect of strategic pricing considerations at the credit committee on the relation between the ratification of loans at the credit committee and two loan outcomes:
$RATE\_DEV_i = \rho_0 + \rho_1 CREDRSK\_MGR_i + \rho_2 CRED\_COM_i + \rho_3 CREDCOM*TIME\_LOW + CONTROLS_i + \varepsilon_i$ (1A).
$LQC\_ADAPT_i = \rho_0 + \rho_1 CREDRSK\_MGR_i + \rho_2 CRED\_COM_i + \rho_3 CREDCOM*TIME\_LOW + CONTROLS_i + \varepsilon_i$ (1B).
Model 2 examines the extent to which the provision of additional treasury services represents an alternative explanation for discounts on standard loan rates and the greater likelihood of loan quality downgrades when loans require approval from higher hierarchical levels:
$RATE\_DEV_i = \rho_0 + \rho_1 CREDRSK\_MGR_i + \rho_2 CRED\_COM_i + \rho_3 TREASURY\_SERVICES + CONTROLS_i + \varepsilon_i$ (2A).
$LQC\_ADAPT_i = \rho_0 + \rho_1 CREDRSK\_MGR_i + \rho_2 CRED\_COM_i + \rho_3 TREASURY\_SERVICES + CONTROLS_i + \varepsilon_i$ (2B).
T-statistics are based on robust regressions or logistic regressions with clustered standard errors. Industry effects are based on Fama and French (1997) industry classification. ***, **, * corresponds to 1%, 5%, and 10% significance levels (two-tailed).
Variable definitions: RATE_DEV is the actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request. In the logistic regression, LQC_ADAPT is an indicator variable equal to one if there is a downgrade in Loan Quality Code in a one-year period following loan approval, zero otherwise. CREDRSK_MGR is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit risk manager, zero otherwise, CRED_COM is an indicator variable equal to one if the decision rights for loan approval are assigned to the credit committee, zero otherwise, TIMECC_LOW is an indicator variable that proxies for the strategic importance of a loan file and is equal to one if the time span between the moment a loan file is put forward for decision-making at the credit committee and the moment the credit committee convenes to discuss the loan file is lower than the median value (two days), zero otherwise, TREASURY_SERVICES is an indicator variable that proxies for the strategic importance of a loan file and is equal to one if the bank also provides treasury services to the prospective borrowing firm, zero otherwise.

days with a standard deviation of twelve calendar days. For our multivariate analyses, we use a median-split to define an indicator variable (TIME_LOW) equal to one if the time is lower than the median value, zero otherwise. We define an interaction term CREDCOM*TIMELOW which reflects the adjustment to the coefficient CREDCOM for loan files discussed in the credit committee soon after being put forward by a loan officer. Model 1 in Table 8 report the results for the dependent variables loan rate deviations and loan quality downgrades. We find that strategic pricing at the credit committee level does not alter our main findings. Specifically, we find that loan requests discussed by the credit committee soon after being put forward for approval do not exhibit greater deviations from the standard loan rate or face any greater likelihood of loan quality downgrade. The coefficient on the interaction term CRED_COM*TIME_LOW is not significant in both regressions.

An alternative rationale for strategic pricing may be that banks are more inclined to offer discounts on loan rates when they expect to earn rents through the provision of additional services. As we have data on the provision of treasury services to borrowing firms (cash management, working capital management, etc.), we examine whether providing treasury services represents an alternative explanation for our findings. We define an indicator variable (TREASURY_SERVICES) equal to one if the bank also provides treasury services to the respective firm, zero otherwise.[30] Model 2 in Table 8 report our results. When we control for the provision of treasury services, the results show that our main inferences are not affected. In addition, the coefficient on TREASURY_SERVICES is not significant. We repeat the analysis, but now examine how the provision of treasury services affects the decision making at the credit committee level by including an interaction term CREDCOM*TREASURY_SERVICES (not tabulated). The coefficient on CRED_COM remains similar in sign and significance levels compared to our main analyses. For the analysis explaining loan rate deviations, we find a negative coefficient on TREASURY_SERVICES ($p < 0.01$, two-tailed), and a positive coefficient on the interaction term CREDCOM*TREASURY_SERVICES ($p < 0.01$, two-tailed). Given that loan files assigned to the credit committee are loans characterized by high credit risk or high outstanding debt, this could suggest that the provision of treasury services may induce the bank the offer lower loan rates *only* as long as the riskiness of the debt does not become too high and/or the prospective borrower does not have our sample bank as its main bank (indicated by a large debt position of the respective firm at this bank). Overall, the inclusion of our two proxies for strategic pricing does not alter our main inferences.

5. Conclusions

We examine how management control structure affects decision making in a bank setting. The control system in place requires that loan officers run large and risky loans through higher hierarchical levels for approval, while decision rights on other loans are delegated to lower-level loan officers. Our results suggest that loan requests ratified by higher-level officers feature higher discounts on standard loan rates vis-à-vis loans on which loan officers can autonomously decide. We also demonstrate that downward loan quality revisions are more likely to occur when higher-level officers approve the loan application rather than the loan officer.

We offer the following explanation for these results. Our bank reviews loan applications of small businesses. As hard (verifiable) information is in short supply for small businesses, banks strongly rely on soft (nonverifiable) information to make decisions. When loan officers

[30] We test for differences in mean loan rate deviations between client firms that are not provided treasury services versus firms that are provided treasury services. The mean loan rate deviation for firms that are (are not) provided treasury services is -1.33 (-0.79), which is significant ($p < 0.01$, one-tailed). The mean proportion of firms that face loan quality downgrades is also greater for firms that are provided treasury services ($p < 0.01$, one-tailed).

need to seek approval from higher level officers, they are uncertain whether the soft information they present will lead higher-level officers to the same conclusion as the loan officer, i.e., that a loan should be granted. Given that loan officers have incentives to make loans, they may be inclined to present the loan file in an optimistically biased way to convince higher-level officers to approve the loan. Soft information enables loan officers to communicate optimistically with higher-level officers and, in addition, being required to run any further loan rate reduction through the hierarchy makes them more inclined to do so. When they propose a higher discount on a standard loan rate, loan officers in effect increase the range in which they can negotiate the ultimate loan rate with their client firms. Taken together, the evidence suggests that the incentive for loan officers to make loans, in combination with the necessity for higher ranked-officers to rely on soft information in their loan decisions, creates conditions in which information reported by loan officers may become optimistically biased.

We attempt to address several potential caveats in this study.

Specifically, we examine the effects of hierarchical structures on lending decisions at one specific branch of one major European bank. Our sample bank is one of the largest financial institutions in the world, did not receive any form of government bailout throughout the crisis, and is consistently ranked by rating agencies at the highest levels. The procedures for screening and monitoring loans, as well as the credit scoring methodology used, are uniform across all branches. Branches are audited yearly to verify whether they comply with bank-level procedures. Our branch successfully completed all audits during the sample period. Based on the intuition that banks face challenges communicating soft information through their transmission channels (Berger and Udell, 2002; Heider and Inderst, 2012), we believe that the implications of our findings may extend well beyond our specific branch.

It should be emphasized that loans are not randomly assigned to hierarchical levels. We control for credit risk and outstanding debt in our empirical analyses in a linear and non-linear way. We employ a regression discontinuity design where we compare a subset of loan files that are similar in credit risk and outstanding debt (just below or above the threshold that distinguishes whether loans can be approved by loan officers or require approval by higher-level officers). We perform a range of robustness analyses to rule out alternative explanations. The robustness checks we deploy however provide little support for the idea that our results could be subject to alternative explanations. In addition, we find that higher-level decision-making only leads to discounts on loan rates for firms that do not have audited financial reports (since audited reports typically decrease the reliance on soft, nonverifiable information in lending decisions).

We believe that the paper increases our knowledge of how hierarchical structures affect decision-making. Indeed, our paper is one of the few to directly document that lending decisions are affected by the internal decision structure of a bank.

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Appendix A. Variable definitions, 2018

Variable name	Description
RATE_DEV	Actual deviation from the standard loan rate as a percentage of the standard loan rate for a loan request.
LQC_ADAPT	Indicator variable equal to one if there is a downgrade in the Loan Quality Code in a one-year period subsequent to the loan approval, zero otherwise. Definition for Tobit models is an integer bounded between zero and four, where zero denotes no downgrade in the loan quality, one denotes a downgrade from “Continuity” towards “Attention-seeking”, until four, which denotes a downgrade from “Continuity” towards “Discontinuity”.
HIERARCHY	Variable equal to one if the decision rights for loan approval are delegated to the loan officer, equal to two if the decision rights for loan approval are assigned to the credit risk manager, and equal to three if the decision rights are assigned to the credit committee.
CREDRSK_MGR	Indicator variable equal to one if the decision rights for loan approval of a loan request are assigned to the credit risk manager, zero otherwise.
CRED_COM	Indicator variable equal to one if the decision rights for loan approval of a loan request are assigned to the credit committee, zero otherwise.
OUTST_DEBT	Natural logarithm of total debt borrowed by firm at the respective bank.
HIGHER_LEVEL	Indicator variable equal to one if the authority for loan approval is assigned to the credit risk manager or credit committee, zero if the authority lies with the loan officer.
CRED_RISK	Internal credit risk assessment of a loan request which captures the likelihood of default and the loss given default (i.e., the amount and quality of collateral).
RISK_SCORE	Internal bank assessment of likelihood of default for loan request.
COLLATERAL	Inverse of internal assessment of loss given default for loan request.
SIZE	Natural logarithm of number of employees of a borrowing firm.
DIST	Indicator variable equal to one if the geographical distance between the bank and the borrowing firm is higher than the median value, zero otherwise.
PRIOR_REL	Indicator variable equal to one if a client firm has a past borrowing relationship with the bank, zero otherwise.
Y2008	Indicator variable equal to one if the loan request is approved in the year 2008, zero otherwise.
LOW_#LOANS	Indicator variable that proxies for the quality of decision-making at the credit committee and is equal to one if one loan file is to be discussed at a credit committee meeting, zero otherwise.
HIGH_CCSIZE	Indicator variable that proxies for the quality of decision-making at the credit committee and is equal to one if five officers attend the credit committee meeting, zero otherwise.
HIGH_TENURE	Indicator variable that proxies for the quality of decision-making at the credit committee and is equal to one if the branch-specific tenure of members that attend the meeting is higher or equal to 14 years, zero otherwise.

HIGH_AGE	Indicator variable that proxies for the quality of decision-making at the credit committee and is equal to one if the average age (experience) of members that attend a meeting is higher or equal to 45 years, zero otherwise.
TIME_LOW	Indicator variable that proxies for the strategic importance of a loan file and is equal to one if the time span between the moment a loan file is put forward for decision-making at the credit committee and the moment the credit committee convenes to discuss the loan file is lower than the median value (i.e., two days), zero otherwise.
TREASURY_SERVICES	Indicator variable that proxies for the strategic importance of a loan file and is equal to one if the bank also provides treasury services to the prospective borrowing firm, zero otherwise.

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