Loan Prospecting*

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Abstract

We analyze corporate lending when loan officers must be incentivized to prospect for loans and to transmit the soft information they obtain in that process. We explore how this multi-task agency problem shapes loan officers' compensation, banks' use of soft information in credit approval, and their lending standards. When competition intensifies, prospecting for loans becomes more important and banks' internal agency problem worsens. In response to more competition, banks lower lending standards, may choose to disregard soft and use only hard information in their credit approval, and in that case reduce loan officers to salespeople with steep, volume-based compensation. Our model generates "excessive lending" as banks' optimal response to an internal agency problem.

Most theories of banking hold the view that a bank faces a given demand for credit, so that the primary role of its staff is to screen applicants and monitor outstanding loans (cf. Freixas and Rochet, 2008). This view seems incomplete. Commercial loan officers spend much time - and are remunerated accordingly - prospecting for new loan-making opportunities or contacting clients to expand existing business. For example, the US Department of Labor describes the job of a loan officer as follows:[1]

> "In many instances, loan officers act as salespeople. Commercial loan officers, for example, contact firms to determine their needs for loans. If a firm is seeking new funds, the loan officer will try to persuade the company to obtain the loan from his or her institution. [...] The form of compensation for loan officers varies. Most are paid a commission that is based on the number of loans they originate. In this way, commissions are used to motivate loan officers to bring in more loans. Some institutions pay only salaries, while others pay their loan officers a salary plus a commission or bonus based on the number of loans originated."

The preceding description suggests a potentially large variation in the compensation practices of loan officers across institutions. Some institutions pursue the strategy of using loan officers more as "salespeople". Wells Fargo, for example, has since the 1980s practiced a model of sending out loan officers to potential borrowers, "armed with a laptop computer [...] to plug in the borrower's information into the computer model – and, in many cases, to approve loans on the spot" (James and Houston, 1996). More generally, loan officers' prospecting effort may constitute an important strategic dimension that has hitherto been largely ignored in the banking literature.

Prospecting for loans interacts with another task that loan officers may perform: screening loan applicants. By virtue of their direct contract with potential borrowers, loan officers generate "soft information", i.e., information that is "hard to quantify, verify and communicate through the normal transmission channels of a banking organization" (Berger and Udell, 2002). We analyze the multi-task problem of both generating lending opportunities and truthfully feeding soft information about those opportunities into the bank's credit approval decision. Our analysis derives joint predictions on banks' use of soft and hard information, loan officers' compensation, and lending standards. In particular, we build on the tension between the different tasks of loan officers to explore two important developments in the banking industry over the last decades: the increase in competition, frequently due to deregulation (cf. Stiroh and Strahan, 2003), and the spread of credit scoring in commercial lending (cf. Berger, Frame and Miller, 2005; Berger, Cowan and Frame, 2011).

Credit scoring provides hard information that is easily communicated within an organization. We show how competition exacerbates the tension between incentivizing loan officers to prospect for loans and incentivizing them to truthfully reveal soft information. In our model, competition may render the use of soft information unprofitable for the bank, even though the information is readily available and its use would allow the bank to better screen out bad loans. The result that competition leads to more reliance on hard information complements the common notion that greater availability and use of hard information allows to bridge the distance between lenders and borrowers, thus leading to more competition (Petersen and Rajan, 2002). Taken together, competition and lending based primarily on hard information are then complementary, mutually reinforcing developments, which may explain why the adoption of credit scoring in commercial lending has not gathered pace equally across countries.

Part of the innovation of our model is that we embed the bank's contracting problem with loan officers into a model of competition that isolates the role of loan officers' prospecting effort. To be specific, our model takes a local incumbent bank whose loan officer can preempt incoming rivals by directly contacting prospective borrowers. Without the threat of competition, there is no need to prospect for loans since any prospective borrower will sooner or later end up at the incumbent's doorstep anyway. Our measures of competitiveness are both the likelihood with which rival banks contact prospective borrowers on the incumbent's turf and rivals' loan terms. Our model generates a loan demand for the incumbent bank that is also a function of its loan officer's prospecting effort. Demand becomes more elastic as competition increases. A more elastic loan demand in turn makes it more profitable for the bank to incentivize its loan officer to exert higher prospecting effort. This feeds back into the contracting model of the bank's internal agency problem. Ultimately, a bank's optimal response to more intense competition is to lower its lending standard and to disregard soft information, so that loan officers act like salespeople with steep, volume-based compensation.

In our model, banks tolerate ex-ante losses on some loans as this relaxes their internal agency problems vis-á-vis loan officers. To our knowledge, this take on potentially "excessive lending" by banks is novel. It relies crucially on acknowledging that a key task of loan officers is to prospect for loans. Rajan (1994) obtains "excessive lending" when bank managers want to influence the market's perception of their ability, while in Berger and Udell (2004) it arises when the ability of loan officers to screen out bad loans deteriorates over time ("loss of institutional memory").

We find that competition affects lending standards via the moral-hazard problem of loan prospecting. Importantly, in our model competition affects the lending standards of an incumbent bank. A number of papers have examined how banking competition lowers the average loan quality due to adverse selection problems, in particular for entrants (Broecker, 1990, Dell'Ariccia, Friedman and Marquez, 1999, and Bofondi and Gobbi, 2006). Other papers analyze how the screening of borrowers varies with changes in the pool of borrowers over the business cycle (Ruckes 2004, Dell'Ariccia and Marquez, 2006).[2]

Our paper also contributes to the recent literature that opens up the "black box" of banks' internal lending processes. Berger, Miller, Petersen, Rajan, and Stein (2005), Stein (2002), and Liberti and Mian (2009) analyze the role of banks' organizational design in the collection and use of information by its staff. Loranth and Morrison (2010) examine the interaction of loan officer compensation and the design of banks' internal reporting systems. Agarwal and Wang (2009) analyze the introduction of piece-rate compensation for small-business loan officers. Banerjee, Cole, and Duflo (2009) and Herztberg, Liberti and Parasivini (2010) analyze a bank's optimal organizational responses to the potential of collusion between loan officers and borrowers.

Our analysis of contracting between a bank and its loan officer is based on a multi-task model (Holmström and Milgrom, 1991). More specifically, the analysis combines a moral-hazard problem (loan prospecting) and a problem with (interim) private information (revealing soft information). This combination of agency problems borrows heavily from the analysis in Dewatripont and Tirole (1999) and, most closely related, Levitt and Snyder (1997).[3] The key insight from the contracting model is that higher incentives to prospect for loans make it more difficult to elicit negative soft information about the lending opportunity that was generated. The loan officer's bias arises endogenously and the bank will counter it by adjusting his compensation, though at the cost of leaving him rents.

The rest of this paper is organized as follows. Section 1 introduces the baseline model. Section 2 analyzes the contracting problem and characterizes the optimal compensation schemes the bank gives to its loan officer under different lending standards. Section 3 embeds the contracting problem in our model of competition and derives the equilibrium choice of compensation, use of information, and lending standard. Section 4 obtains additional implications by introducing a loan-review stage. Section 5 extends the model to allow for a richer notion of soft information in order to sharpen our conclusion on "excessive lending". Section 6 introduces competition in loan rates in addition to competition in loan prospecting. We conclude in Section 7.

1 Baseline Model

The heart of our model of loan-making is an internal agency conflict of the bank. The bank must give its loan officer incentives to perform two tasks: generate loan-making opportunities and possibly use soft information to enhance the bank's loan approval decision.

Loan Prospecting. The loan officer can generate a new loan-making opportunity with probability $q(e)$ by exerting a non-observable effort e at a private cost $c(e)$. We provide a foundation of $q(e)$ in terms of banking competition, together with a comparative analysis, in Section 3 after we have derived the contracting equilibrium in Section 2. To simplify the exposition, we stipulate that $e \in [0, 1]$ and that $c(e)$ and $q(e)$ are continuously differentiable with $c'(0) = 0$, $q'(0) > 0$, $c'' > 0$, and $q'' \leq 0$, while $c'(1)$ is assumed to be sufficiently large to generate an interior solution.

Borrower Types. A potential new borrower can have two types, $\theta \in \Theta = \{\underline{\theta}, \overline{\theta}\}$, that determine the probability with which the borrower will succeed, $\underline{p}$ and $\overline{p}$, respectively. The repayments to the bank in case of success and failure, $R \in \{R^s, R^f\}$ are independent of the borrower type. These repayments are presently taken as given (we relax this in Section 6). The ex-ante probability of being a high type is denoted by μ_0. The loan size is $k > 0$. A loan to a low-type borrower has negative net present value (NPV) for the bank while a loan to a high-type borrower has positive NPV. Without affecting our results qualitatively, it is then convenient to set $R^f = 0$ and $\underline{p} = 0$: A borrower repays zero in case of default, e.g., as he is penniless and there is no pledgeable collateral, and a low-type borrower has a zero probability of success. To simplify the notation, we write $\overline{p} = p$ for the high-type borrower. The NPV of the high-type borrower then is $v = pR^s - k$ while the NPV of a low-type borrower is simply $-k$ (we abstract from discounting).

Denote by μ^* the proportion of high-type borrowers at which the bank just breaks even, $\mu^* v + (1-\mu^*)(-k) = 0$, or

$$\mu^* = \frac{k}{pR^s}. \tag{1}$$

Information. At the loan approval stage, two types of information are obtained: hard information, which is verifiable, and soft information, which is privately observed by the loan officer. Hard information is captured by a signal $h \in \{\underline{h}, \overline{h}\}$, which is generated with precision ρ_H, where

$$\rho_H = \Pr[\overline{h}|\overline{\theta}] = \Pr[\underline{h}|\underline{\theta}] \tag{2}$$

and $1/2 < \rho_H < 1$. Analogously, soft information is captured by a signal $s \in \{\underline{s}, \overline{s}\}$ with precision $1/2 < \rho_S < 1$ (we relax this in Section 5). Based on a pair of signals (s, h) and the prior μ_0, we obtain posterior probabilities about types, $\Pr[\theta|s,h]$. For example, when both soft and hard information are positive, $s = \overline{s}$ and $h = \overline{h}$, then

$$\Pr[\overline{\theta}|\overline{s}, \overline{h}] = \frac{\rho_S \rho_H \mu_0}{\rho_S \rho_H \mu_0 + (1-\rho_S)(1-\rho_H)(1-\mu_0)}. \tag{3}$$

In this case, for instance, the posterior probability of non-default is $\Pr[\overline{\theta}|s,h]p$.

We stipulate that the bank can lend profitably only when both hard and soft information are positive, $\Pr[\overline{\theta}|\overline{s}, \overline{h}] > \mu^*$. Note that when $\rho_H = \rho_S = \rho$, so that $\Pr[\overline{\theta}|\overline{s}, \underline{h}] = \Pr[\overline{\theta}|\underline{s}, \overline{h}] = \mu_0$, this is satisfied whenever $\mu_0 < \mu^*$, i.e., whenever the bank can not make profits by approving loans indiscriminately.

Contracting. At the loan approval stage, a deterministic mechanism specifies a decision by the bank to accept or reject the loan depending on the verifiable hard information h and the soft information that was *communicated* by the agent, denoted by $\hat{s} \in \{\underline{s}, \overline{s}\}$. The set of all possible combinations of information that the bank faces is $\Omega = (\underline{s}, \overline{s}) \times (\underline{h}, \overline{h})$. We denote the set of all $(\hat{s}, h) \in \Omega$ for which the bank accepts the loan by A. For example, if the bank approves a loan only when hard information is positive, then $A = \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}$.

The prior probability for each element in Ω is obtained from the prior about types μ_0 and the signal precision levels ρ_S and ρ_H. For example, the probability that both soft and hard information will be positive is

$$\Pr[\overline{s}, \overline{h}] = \mu_0 \rho_S \rho_H + (1 - \mu_0)(1 - \rho_S)(1 - \rho_H). \tag{4}$$

In addition to the loan acceptance set, the mechanism also specifies a compensation for the loan officer. When a loan is made, we allow compensation to depend on hard information, on revealed soft information, and on the borrower's repayment, $w(\hat{s}, h; R)$ when $(\hat{s}, h) \in A$. The key contractual restriction, which we discuss next in detail, is that when no loan is made, *either* because it was not generated *or* because it was rejected, the agent receives the same compensation, $\underline{w}$. We further assume that the loan officer is protected by limited liability, so that $w(\hat{s}, h; R) \geq 0$ and $\underline{w} \geq 0$.

In our model, the loan officer can affect the quality of loans that the bank approves by strategically communicating his soft information. However, our analysis applies generally to situations in which loan officers can distort information, e.g., by conspiring with borrowers. What is important, though, is that a bank's incentive scheme cannot remunerate loan officers separately for the different tasks they perform. In the context of our model, such a separation would require the bank to condition pay directly on loan applications. In practice, conditioning pay on applications may be not be feasible or it may create problems of its own. For instance, banks may want loan officers to pre-assess potential borrowers before a formal, more costly application process is started.[4] Also, when loan officers are paid conditional on the loan applications they generated, then this may induce them to target borrowers who are more likely to apply, but who may ultimately be less credit-worthy or who turn down a loan offer after a costly loan application process.[5] After characterizing the optimal compensation contract in Section 2, we return to a discussion of the robustness of our results.

Timing. The timing of the game is as follows. The bank offers the loan officer a contract at $t = 0$. The contract determines the bank's loan-approval decision A and the loan officer's compensation scheme $w(\hat{s}, h; R)$ and $\underline{w}$. When the loan officer accepts, he exerts effort e at $t = 1$, which generates a loan making opportunity at $t = 2$ with probability $q(e)$. When a loan making opportunity exists, the loan officer communicates his soft information about the borrower in addition to the observable hard information, and the bank decides whether to approve the loan or not. If a loan is made, the borrower repays R at $t = 3$, depending on the success or failure of his project. This is also when the loan officer receives his compensation. All parties are risk neutral.

2 Compensation and Loan Approval

In this Section, we derive the bank's cost of implementing a certain level of prospecting effort e^* by the loan officer, taking the loan-approval decision A as given. The bank implements the loan officer's effort by choosing an appropriate compensation scheme $w(\hat{s}, h; R)$ and $\underline{w}$. However, the bank has to take into account also the effect the compensation scheme has on the loan officer's incentives to communicate soft information, provided that it is used in the bank's loan-approval decision.

2.1 The Bank's Program

To derive the bank's optimization problem, we first consider the loan officer's incentive to exert prospecting effort. When a loan is made, knowing both the hard and the true soft information, the loan officer's expectation of his compensation is

$$E[w(\hat{s}, h)|s] = \Pr[\overline{\theta}|s, h] p w(\hat{s}, h; R^s) + \left(1 - \Pr[\overline{\theta}|s, h] p\right) w(\hat{s}, h; 0), \tag{5}$$

where s is the true soft information and $\hat{s}$ is what he communicates to the bank. According to the Revelation Principle, we can restrict ourselves to the case in which the loan officer truthfully reveals his soft information. In order for the loan officer to truthfully reveal his soft information for a given loan-approval regime A, his compensation scheme must satisfy the following incentive constraints:

$$\begin{aligned} &\text{i) For all} \quad (s,h) \in A, (\hat{s},h) \in \Omega : E[w(s,h)|s] \geq \max\{E[w(\hat{s},h)|s], \underline{w}\} \\ &\text{ii) For all} \quad (s,h) \in \Omega \backslash A, (\hat{s},h) \in A : \underline{w} \geq E[w(\hat{s},h)|s]. \end{aligned} \tag{IC_T}$$

Part i) says that the loan officer must prefer to tell the truth when doing so leads to the acceptance of the loan while lying leads either to acceptance or rejection. Part ii) says that he must prefer to tell the truth when doing so leads to the rejection of the loan. When the truth-telling constraints are satisfied, then $\hat{s} = s$ and we simply write $E[w(s,h)]$ for the loan officer's expected payment when a loan is made (cf. expression (5)).

The loan officer's optimal level of effort is given by

$$e^* = \arg\max_e \left\{ q(e) \sum_{(s,h)\in A} \Pr[s,h] E[w\,(s,h)] + \left[1 - q(e) \sum_{(s,h)\in A} \Pr[s,h] \right] \underline{w} - c(e) \right\}, \tag{6}$$

where we used that the compensation $\underline{w}$ is paid either when no loan was generated or when a loan application was rejected.[6] The corresponding first-order condition yields the incentive constraint:

$$\sum_{(s,h)\in A} \Pr[s,h] \left[E[w\,(s,h)] - \underline{w} \right] = \frac{c'(e^*)}{q'(e^*)}. \tag{IC_e}$$

The strict convexity of $c(e)$ and strict concavity of $q(e)$ yield a unique effort level e^* for a given loan-approval regime A. According to condition IC_e in order to induce effort e^*, the expected compensation must be sufficiently larger when a loan is made than when it is not.

Given the loan officer's level of effort e^* and given a loan-approval scheme A, the optimal compensation scheme minimizes the bank's expected cost,

$$K(e^*; A) = q(e^*) \sum_{(s,h)\in A} \Pr[s,h] E[w(s,h)] + \left[1 - q(e) \sum_{(s,h)\in A} \Pr[s,h]\right] \underline{w}, \tag{7}$$

subject to the incentive constraint IC_e, the truth-telling constraints IC_T, and the limited liability constraints $w(s,h;R) \geq 0$ and $\underline{w} \geq 0$.

Once we have determined the optimal compensation scheme, we derive the level of effort that the bank wants to implement for a given loan approval regime A. The optimal level of effort maximizes bank profits,[7]

$$\Pi(e^*; A) = q(e^*) \left[\sum_{(s,h)\in A} \Pr[s,h] \left(\Pr[\overline{\theta}|s,h] p R^s - k\right)\right] - K(e^*; A). \tag{8}$$

In a final step, which is relegated to Section 3, we solve for the optimal acceptance set A^* that maximizes bank profits when effort and compensation are optimally chosen.

In what follows, we first work under the assumption that the bank optimally chooses only between two lending regimes: $A = \left\{(\overline{s}, \overline{h}), \left(\underline{s}, \overline{h}\right)\right\}$ and $A = \{(\overline{s}, \overline{h})\}$. We prove this formally when we characterize the equilibrium in Proposition 3. That is, the bank either uses the loan officer's privately observed soft information to apply a strict loan-approval policy with $A = \{(\overline{s}, \overline{h})\}$, or it relies only on hard information to screen out bad applicants, $A = \left\{(\overline{s}, \overline{h}), \left(\underline{s}, \overline{h}\right)\right\}$. Recall that the bank needs to use soft information to achieve the unconstrained optimal approval decision, $A = \{(\overline{s}, \overline{h})\}$.

2.2 Optimal Compensation

Hard-Information Lending. When the bank relies only on hard information, $A = \left\{(\overline{s}, \overline{h}), \left(\underline{s}, \overline{h}\right)\right\}$, the truth-telling constraints IC_T are redundant. The loan officer's optimal compensation need not elicit his soft information. It must induce him only to exert an effort level e^*. The following is then immediate from the incentive constraint for effort IC_e.

Proposition 1 *Suppose the bank wants to incentivize the loan officer to undertake the prospecting effort e^*. Then with hard-information lending, $A = \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}$, it is optimal to pay the loan officer a (piece-rate) compensation per approved loan,*

$$W = \sum_{(s,h)\in A} \Pr[s,h] E[w(s,h)] = \frac{c'(e^*)}{q'(e^*)}, \tag{9}$$

and nothing otherwise, $\underline{w} = 0$.

In Proposition 1 we have simplified our notation and denoted by W the piece-rate compensation per approved loan. Since the wage $\underline{w}$ hurts the officer's incentives to generate loans, the bank optimally sets it to zero. The bank's expected cost of inducing an effort level e^* under hard-information lending is

$$K\left(e^*; \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}\right) = K_H(e^*) = q(e^*)\frac{c'(e^*)}{q'(e^*)}. \tag{10}$$

The piece-rate pay W and hence the incentive cost $K_H(e^*)$ are increasing with effort since $\frac{c'(e^*)}{q'(e^*)}$ is increasing in e^*. Observe also that the compensation cost of incentivizing the loan officer to exert the effort level e^* is larger than the cost of effort itself, $q(e^*)\frac{c'(e^*)}{q'(e^*)} > c(e^*)$, i.e., the loan officer obtains a rent when his effort level is not observable.

Soft-Information Lending.[8] When the bank uses soft information in addition to hard information, $A = \{(\overline{s}, \overline{h})\}$, the truth-telling constraints IC_T are relevant and become

$$E[w(\overline{s}, \overline{h})] \geq \underline{w}, \tag{11}$$

$$\underline{w} \geq E[w(\overline{s}, \overline{h}) | \underline{s}]. \tag{12}$$

Consider first constraint (11). When both hard and soft information are positive, $(s, h) = (\overline{s}, \overline{h})$, and the loan officer tells the truth, the loan is accepted and the loan officer expects to be paid $E[w(\overline{s},\overline{h})]$. If the loan officer lies, so that the loan is rejected, he is paid $\underline{w}$. Hence, truth-telling requires $E[w(\overline{s},\overline{h})] \geq \underline{w}$ when $(s,h) = (\overline{s},\overline{h})$. Consider next constraint (12). When only hard information is positive, $(s,h) = (\underline{s},\overline{h})$, the loan officer must prefer the wage $\underline{w}$ to the expected pay $E[w(\overline{s},\overline{h})\,|\underline{s}]$ since truth-telling leads to loan rejection whereas lying leads to loan acceptance. Note finally that when hard information is negative, $(s,h) = (s,\underline{h})$, the loan is always rejected and the bank does not need to elicit soft information. Hence, conditions (11) and (12) completely capture the truth-telling constraints IC_T.

With soft information lending, the incentive constraint IC_e becomes

$$\Pr[\overline{s},\overline{h}]\left[E[w(\overline{s},\overline{h})] - \underline{w}\right] = \frac{c'(e^*)}{q'(e^*)}, \tag{13}$$

since the loan officer receives the pay $w(s,h;R)$ only when both soft and hard information are positive. The following proposition characterizes the optimal compensation scheme with soft-information lending:[9]

Proposition 2 *Suppose the bank wants to incentivize the loan officer to undertake the prospecting effort e^*. Then with soft-information lending, $A = \{(\overline{s},\overline{h})\}$, the optimal compensation scheme consists of i) pay for loans that are made and perform and ii) pay when no loan is made:*

$$\begin{aligned}
w(\overline{s},\overline{h};R^s) &= \overline{w} = \frac{c'(e^*)}{q'(e^*)}\frac{1}{p}\frac{1}{\Pr[\overline{s},\overline{h}]\left(\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]\right)}, && (14)\\
w(\overline{s},\overline{h};0) &= 0, && (15)\\
\underline{w} &= \frac{c'(e^*)}{q'(e^*)}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{s},\overline{h}]\left(\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]\right)}. && (16)
\end{aligned}$$

Proof. See Appendix.

The loan officer must receive some positive pay $\underline{w}$ to induce truth-telling when soft information is negative and the loan is rejected (condition (12)). A higher pay $\underline{w}$, however, undermines his incentives to generate loan-making opportunities in the first-place (condition (13)). Hence, the bank sets the pay $\underline{w}$ as low as condition (12) allows. To counter the negative incentive effect of the pay $\underline{w}$, the bank must increase its pay when a loan is made. The cheapest way to provide such pay is to give a bonus when the borrower succeeds, $w(\overline{s}, \overline{h}; 0) = 0$, since the probability of failure is larger when the loan officer lies, $1 - \Pr[\overline{\theta}|\underline{s}, \overline{h}]p > 1 - \Pr[\overline{\theta}|\overline{s}, \overline{h}]p$. Thus, setting $w(\overline{s}, \overline{h}; R^s) > w(\overline{s}, \overline{h}; 0) = 0$ minimizes the bank's cost of compensation when the loan officer wrongly pretends that soft information is positive.

From Proposition 2, the ratio $\frac{\overline{w}}{\underline{w}}$ of pay when a (successful) loan is made and when it is not made, is given by

$$\frac{\overline{w}}{\underline{w}} = \frac{1}{\Pr[\overline{\theta}|\underline{s}, \overline{h}]p} > 1, \tag{17}$$

where the term in the denominator is the conditional probability that a loan would perform *if* it was wrongly approved after bad soft information. When this is higher, though still sufficiently low so that the respective NPV is negative, the ratio must be lower so as to keep the loan officer from lying about bad soft information.

Comparison. Substituting from Proposition 2, the bank's expected cost of implementing an effort level e^* by the loan officer under soft information lending becomes

$$K\left(e^*; \{(\overline{s}, \overline{h})\}\right) = K_S(e^*) = \frac{c'(e^*)}{q'(e^*)}\left[q(e^*) + \frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{s}, \overline{h}]\left(\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}\right)]}\right]. \tag{18}$$

Thus, the cost of compensation now contains both the incentive component $K_H(e^*) = q(e^*)\frac{c'(e^*)}{q'(e^*)}$ to generate loans and the additional cost of inducing the loan officer to reveal his soft information truthfully,

$$K_S(e^*) - K_H(e^*) = \underline{w} = \frac{c'(e^*)}{q'(e^*)} \frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{s}, \overline{h}]\left(\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}\right)]}. \tag{19}$$

The additional cost of eliciting soft information is given by the base wage $\underline{w}$ and it increases with effort. To induce a higher effort from the loan officer, the bank must increase the wedge between the expected pay he obtains when a loan is accepted and when it is rejected (condition (13)). A higher wedge, however, increases the loan officer's incentive to lie about his soft information (condition (12)). The bank must, therefore, increase also the base wage and, hence, the rent the loan officer receives. In fact, we know from expression (17) that preserving truth-telling incentives requires the bank to keep the ratio $\frac{\overline{w}}{\underline{w}}$ constant.

For future reference, we state the preceding observations formally.

Corollary 1 *The expected cost of inducing a higher level of prospecting effort, e^*, increases under both hard- and soft-information lending. Moreover, the additional cost of eliciting soft information, $K_S(e^*) - K_H(e^*)$, also increases with effort.*

Discussion of Mechanism We have made two key specifications about the contracting environment in our model. First, we take a mechanism-design approach where compensation and, in particular, the loan approval decision can be verifiably conditioned on hard information, as well as on the soft information revealed by the loan officer (his "message"). Second, the loan officer receives a single level of pay when no loan is made, irrespective of whether there is no loan application or an application is rejected.

It may be argued that while hard information, as well as the communicated soft information, are both observable to the bank, this may not be true for outsiders such as courts. After all, a bank's scoring rule should be its private information. In that case, it would be appropriate to solve for a game in which the bank cannot commit to a loan approval decision. Nevertheless, our preceding characterization carries over since, as we now show, there is no commitment problem for the bank. Under hard-information lending, the bank strictly prefers not to approve a loan when $h = \underline{h}$. Whether the bank wants to approve a loan when $h = \overline{h}$ depends on the amount of compensation W that is necessary to induce an effort level e^*. Although the compensation W may not be low enough to approve a loan for an *arbitrary* effort level e^*, this cannot be the case for the *optimal* choice of e^* as the bank makes profits from lending. The same argument applies to soft-information lending.

Hence, even when hard-information is not verifiable by outsiders, we obtain the same outcome as characterized before. This observation has also the following implication. Recall our restriction that the loan officer receives the same wage $\underline{w}$ regardless of whether an application was rejected or not generated in the first place. We argued above that when paying the loan officer separately for each new application, this would distort incentives as he would then, for instance, turn to more easily accessible though ultimately less promising borrowers. When hard information was verifiable, the bank could partly forestall this by only paying for an application when this generated positive hard information. This, however, is no longer feasible when, as we currently assume, hard information is not verifiable by outsiders. This observation further supports our restriction to the characterized simple compensation.

3 Equilibrium

In this section, we jointly determine the optimal lending regime and the optimal level of prospecting effort that the bank wants to induce. We do so in a model of competition that endogenizes how prospecting affects the demand for loans. This allows to conduct a comparative analysis of the lending regime and loan officer compensation in terms of competition in the loan market.

3.1 Competition and Loan Prospecting

Consider a local lender who must compete to defend his turf. The analysis in this section focuses on the loan officer's prospecting effort as the main strategic variable and isolates the effect of competition through the acquisition of new lending opportunities. We examine loan rate (price) competition, which is the standard channel hitherto examined in the literature, in Section 6.

The competition model consists of three sub-periods, $\tau = 1, 2, 3$, that play out in $t = 1$, i.e., after the loan officer's compensation contract was signed in $t = 0$ and before soft and hard information are obtained from a potential borrower in $t = 2$.

Suppose for simplicity that there is a single potential borrower. At $\tau = 3$, the borrower himself becomes aware of his need for a loan and turns to the local lender. Consequently, if there was no alternative outside lender, loan prospecting by the incumbent local lender would be irrelevant. Eventually, the borrower realizes his need and turns up at the local lender's doorstep. Indeed, the idea of a borrower himself contacting potential lenders prevails in the literature. Instead, we suppose that a distant lender can enter and contact the borrower at $\tau = 2$. The contact happens with probability λ_E and leads to the loss of the borrower for the local lender (cf., however, the extension in Section 6). To preempt the loss, the incumbent lender induces its loan officer to exert a prospecting effort e in order to contact the potential borrower first at $\tau = 1$. The local lender's preemptive contact occurs with probability $\lambda_I(e)$, where $\lambda_I' > 0$ and $\lambda_I'' \leq 0$. The overall probability for the local lender to have a loan-making opportunity, either at $\tau = 1$ or at $\tau = 3$, is therefore

$$q(e) = [1 - \lambda_E] + \lambda_E \lambda_I(e). \tag{20}$$

Equation (20) connects the competition analysis with the contracting analysis of the previous Section. The equation bears close resemblance to standard demand functions. The elasticity with respect to the prospecting effort is

$$\eta(e) = \frac{q'(e)}{q(e)} e = \frac{\lambda_I' \lambda_E}{[1 - \lambda_E] + \lambda_E \lambda_I(e)} e. \tag{21}$$

The elasticity strictly increases in the prospecting of the rival lender, λ_E, which is our measure of competition in this Section. The reason it that first, when λ_E increases, the level $q(e)$ decreases, i.e., "demand" shifts inwards as competition increases. Second, the derivative $q'(e) = \lambda_E \lambda_I'$ increases, i.e., "demand" becomes more responsive to the local lender's own strategic variable: the loan prospecting effort e. To obtain explicit expressions, it is convenient to use a linear-quadratic specification with

$$c(e) = \frac{1}{2\gamma} e^2, \quad \lambda_I(e) = e, \tag{22}$$

and hence

$$\eta(e) = \frac{\lambda_E e}{1 - \lambda_E (1-e)}. \tag{23}$$

3.2 Optimal Loan Prospecting

We now solve for the optimal prospecting effort that the bank wants to implement under both hard- and soft-information lending. Comparing the bank's profits at these effort levels then establishes when either regime is optimal.

Hard-Information Lending. When the bank uses only hard information in the loan approval decision, $A_H = \left\{ (\overline{s}, \overline{h}), \left(\underline{s}, \overline{h}\right) \right\}$, the prospecting effort it wants to implement maximizes

$$\Pi(e^*; A_H) = q(e^*) \left[\sum_{(s,h) \in A_H} \Pr[s,h] \left(\Pr[\overline{\theta}|s,h] p R^s - k \right) - \frac{c'(e^*)}{q'(e^*)} \right]. \tag{24}$$

The following Lemma states the solution to the maximization problem:

Lemma 1 *Under hard-information lending, the bank optimally induces the loan officer to exert prospecting effort*

$$e_H^* = \frac{1}{2} \gamma \lambda_E \left(\sum_{(s,h) \in A_H} \Pr[s,h] \left(\Pr[\overline{\theta}|s,h] p R^s - k \right) - \frac{1-\lambda_E}{\gamma \lambda_E^2} \right), \tag{25}$$

when the term in brackets is positive. Otherwise, $e_H^* = 0$. Higher competition (higher λ_E) increases optimal prospecting effort e_H^* and relaxes the condition for a positive effort.

Proof. See Appendix.

Competition affects the bank's choice of the optimal prospecting effort through two channels. First, higher competition increases the marginal benefit of prospecting effort: $q'(e) = \lambda_E$. This is an immediate implication of our model of prospecting, where the benefit from prospecting is to forestall competition. The second channel works through the agency problem. More intense competition reduces both the bank's cost of inducing a given level of prospecting effort $K_H(e^*)$ (and hence reduces the loan officer's rent $K_H(e^*) - c(e^*)$) and its marginal cost of inducing a higher level of effort $K'_H(e^*)$. To see this, recall that $K_H(e^*) = q(e^*)c'(e^*)/q'(e^*)$ and that more intense competition increases the responsiveness of "demand" (higher $q'(e)$) as well as shifts "demand" inwards (lower $q(e^*)$). The bank's marginal cost of inducing effort is

$$\begin{aligned} \frac{dK_H(e^*)}{de^*} &= c'(e^*) + q(e^*)\frac{q'(e^*)c''(e^*) - q''(e^*)c'(e^*)}{q'(e^*)^2} && (26) \\ &= \frac{1}{\gamma}e^* + \frac{1}{\gamma}\left[\frac{1}{\lambda_E} - (1 - e^*)\right], && (27) \end{aligned}$$

which is strictly decreasing in λ_E. Interestingly, both channels (marginal benefit of prospecting and agency cost) can also be seen when rewriting the expression from Lemma 1 as follows

$$e_H^* = \gamma \frac{1}{1 + \eta^{-1}(e_H^*)} \left(\lambda_E \sum_{(s,h) \in A_H} \Pr[s,h] \left(\Pr[\overline{\theta}|s,h] p R^s - k \right) \right), \tag{28}$$

since the elasticity η directly captures the effect of more intense competition on the slope and the location of the demand curve $q(e^*)$.[10]

Soft-Information Lending. When the bank uses soft information in the loan approval decision, $A_S = \left\{(\overline{s}, \overline{h})\right\}$, the optimal prospecting effort maximizes

$$\begin{aligned}\Pi(e^*; A_S) &= q(e^*)\Pr[\overline{s}, \overline{h}]\left(\Pr[\overline{\theta}|\overline{s}, \overline{h}]pR^s - k\right) \\ &\quad -\frac{c'(e^*)}{q'(e^*)}\left[q(e^*) + \frac{1}{\Pr[\overline{s}, \overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}]}\right]. \end{aligned} \tag{29}$$

Lemma 2 derives the optimal prospecting effort with soft information:

Lemma 2 *Under soft-information lending, the bank optimally induces the loan officer to exert prospecting effort*

$$e_S^* = \frac{1}{2}\gamma\lambda_E\left(\Pr[\overline{s}, \overline{h}]\left(\Pr[\overline{\theta}|\overline{s}, \overline{h}]pR^s - k\right) - \frac{1-\lambda_E}{\gamma\lambda_E^2} - \frac{1}{\gamma\lambda_E^2}\frac{1}{\Pr[\overline{s}, \overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}]}\right), \tag{30}$$

when the term in brackets is positive. Otherwise, $e_S^* = 0$*. Higher competition (higher* λ_E*) increases optimal prospecting effort* e_S^* *and relaxes the condition for a positive effort.*

Proof. See Appendix.

Compared to hard-information lending, the expression for the optimal prospecting effort with soft-information lending contains an extra term, which is caused by the cost of eliciting the loan officer's soft information (given in (19)).

3.3 Competition and Optimal Lending Regime

So far we only considered hard- and soft information lending ($A = \left\{(\overline{s}, \overline{h}), \left(\underline{s}, \overline{h}\right)\right\}$ or $A = \{(\overline{s}, \overline{h})\}$). Proposition 3 confirms that this is without loss of generality: It is indeed optimal for the bank to accept loan applications only when hard information is positive, or to use soft information to further screen such applications. Building on Lemmas 1 and

2, we now show that the bank switches from soft- to hard information lending when the intensity of competition increases beyond a threshold level.[11]

Proposition 3 *The bank optimally chooses between two lending regimes. Either a loan is approved only when hard information is positive ("hard-information lending", $A = \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}$) or loan approval also requires that the loan officer's soft information is positive ("soft-information lending", $A = \{(\overline{s}, \overline{h})\}$). When either lending regime is optimal for some level of competition λ_E, then there exists a cutoff $0 < \hat{\lambda}_E < 1$, such that the bank prefers the hard-information lending regime when competition is sufficiently intense, $\lambda_E > \hat{\lambda}_E$, while it prefers the soft-information lending regime when $\lambda_E < \hat{\lambda}_E$. At $\lambda_E = \hat{\lambda}_E$ the bank is indifferent.*

Proof. See Appendix.

The intuition for Proposition 3 builds on the observation that more intense competition leads to a higher optimal prospecting effort in both lending regimes (cf. Lemma 1 and Lemma 2). Moreover, a higher prospecting effort increases the cost of eliciting soft information (cf. Corollary 1). Taken together, as the bank optimally responds to more intense competition with higher incentives, it becomes increasingly costly to truthfully elicit soft information, which ultimately induces the bank to rely only on hard information. As noted in the introduction, this observation complements the view prevailing in the literature that (better) use of hard information itself intensifies competition, as it allows banks to overcome distance (cf. Petersen and Rajan, 2002). Taken together, this perspective as well as ours suggest a strong complementarity between increasing competition and the (exclusive) use of hard information in lending.

Further Comparative Analysis. As competition increases, regardless of the lending regime, the bank optimally elicits higher prospecting effort (cf. Lemma 1 and Lemma 2). Furthermore, we can show that as the bank switches towards hard-information lending, i.e., when $\lambda_E = \widehat{\lambda}_E$, the optimally induced prospecting effort changes discontinuously: $e_H^* > e_S^*$ at $\lambda_E = \widehat{\lambda}_E$. Altogether, when we vary λ_E, the prospecting effort that is induced under hard-information lending is thus always strictly higher than the effort under soft-information lending. Loan officers who perform merely the role of salespeople are, in equilibrium, more aggressive in prospecting for new loans. Further, the higher is λ_E, the steeper is their piece-rate compensation scheme (higher W). Recall that under soft-information lending the loan officer's pay depends also on loan performance, and he obtains compensation also when no loan is made ($\underline{w} > 0$; cf. Proposition 2). Still, we can show that when λ_E increases, the "upside" that a loan officer receives under soft-information lending, $\overline{w} - \underline{w}$, also increases.

Finally, note that at $\widehat{\lambda}_E$ there is a discrete shift in the average quality of loans, as soft information is no longer used to screen loans. At $\widehat{\lambda}_E$ loan volume thus strictly increases both as prospecting effort increases and loan approval becomes more likely.

Corollary 2 *As competition intensifies (higher λ_E), prospecting effort increases, average loan quality deteriorates, and the loan officer's incentives become steeper. Precisely:*
i) Prospecting effort everywhere strictly increases with λ_E, and discretely so when the bank optimally switches to hard-information lending.
ii) As the bank switches (at $\lambda_E = \widehat{\lambda}_E$) to hard-information lending, average loan quality deteriorates.
iii) The "upside" in the loan officer's pay (W under hard-information lending and $\overline{w} - \underline{w}$ under soft-information lending) strictly increases with λ_E. For high competition and hard-information lending, the loan officer is compensated only based on loan volume ("piece rate"), while for low competition and soft-information lending he receives a "base wage" next to a bonus that depends also on loan performance.

Proof. See Appendix.

Corollary 2 thus provides joint implications for compensation, the choice of lending regime (use of soft information or not), loan volume, and also the likelihood of default, all in terms of a change in competition as the exogenous variable. As noted in the introduction, casual evidence suggests that loan officers' compensation varies substantially across banks. Our analysis would suggest that the form of compensation is a function of loan officers' tasks. Agarwal and Wang (2009) show in a field experiment that introducing piece-rate compensation for small-business loan officers leads to a higher number of loans being made but also to higher default rates. The effect is stronger when loan applications contain more soft information (see Cole, Kanz, and Klapper, 2010, for related experimental evidence). According to Corollary 2, a switch to hard-information lending would indeed lead to more high-powered incentives, together with an increase in loan volume and higher default rates. In our present comparative analysis, this would be triggered by more intense competition. In Section 5 we show that the joint prediction of steeper incentives and higher default rates through a lower lending standard holds also when, in an extended model, soft information continues to be used as competition increases, albeit to a lesser extent.

4 Loan Review

Up to now, the loan officer's compensation could be made contingent on the performance of the loan, R. For long-term loans such performance pay may be too expensive when the loan officer discounts payments that occur in the distant future more than the bank. We now extend our model to encompass the situation in which the loan officer's compensation is contingent only on some signal of future loan performance, instead of performance itself. Such a signal may arise from a review of the loan by the bank.

To extend the model, we add an additional period and stipulate that the loan repayment R is postponed from $t = 3$ to $t = 4$. For sinplicity, the loan officer derives zero utility from being paid at this late stage. At $t = 3$, a verifiable signal $r \in [\overline{r}, \underline{r}]$ becomes available. It is convenient to specify that r is a noisy signal of soft-information s with precision ψ,

$$\Pr[\overline{r}|\overline{s}] = \Pr[\underline{r}|\underline{s}] = \psi, \tag{31}$$

where $\frac{1}{2} < \psi < 1$, and that r is independent of hard information. For simplicity, we set $p = 1$ so that a high-type borrower $\overline{\theta}$ always repays the loan. We can then think of r as a signal of the borrower type θ: $\Pr[\overline{r}|\overline{\theta}] = \Pr[\underline{r}|\underline{\theta}] = \rho_S\psi + (1-\rho_S)(1-\psi) > \frac{1}{2}$.

The loan officer's compensation is now contingent on the signal r instead of the repayment R. In analogy to expression (5), his expected compensation becomes

$$E[w(\hat{s},h)|s] = \Pr[\overline{r}|s,h]w(\hat{s},h;\overline{r}) + (1 - \Pr[\overline{r}|s,h])\, w(\hat{s},h;\underline{r}). \tag{32}$$

With that change, our analysis applies as before. The hard-information lending regime is not affected since the loan officer's optimal compensation depends on the volume of made loans and not on their performance. In the soft-information regime the structure of compensation is unchanged. It is still optimal to pay a bonus, which the bank now awards when the performance signal is positive, $w(\hat{s},h;\overline{r}) = \overline{w}_r > w(\hat{s},h;\underline{r}) = 0$, and to pay the loan officer a positive amount even when no loan is made, $\underline{w}_r > 0$.[12] The respective amounts are obtained in analogy to Proposition 2, except that they now depend on the probability of a positive signal conditional on the realization of soft and hard information, $\Pr[\overline{r}|s,h]$, rather than the conditional probability of a high-type borrower, $\Pr[\overline{\theta}|s,h]$. Making this replacement and using (31) yields

$$\overline{w}_r = \frac{c'(e^*)}{q'(e^*)} \frac{\psi}{\Pr[\overline{s},\overline{h}]\,(2\psi - 1)} \tag{33}$$

$$\underline{w}_r = \frac{c'(e^*)}{q'(e^*)} \frac{1-\psi}{\Pr[\overline{s},\overline{h}]\,(2\psi - 1)}. \tag{34}$$

The effect of a more precise performance signal is then immediate and stated formally in the following Proposition:

Proposition 4 *Suppose that the loan officer's compensation is contingent on a signal of future loan performance rather than actual performance itself (loan review). As the precision of the signal increases (higher ψ): i) the ratio of bonus pay to base wage under soft-information lending $\frac{\overline{w}_r}{\underline{w}_r}$ increases while the volume pay W under hard-information does not change, ii) the bank's additional cost of eliciting soft information (given by $\underline{w}_r$) decreases, and iii) the competition threshold $\widehat{\lambda}_E$ at which the bank switches from soft- to hard-information lending increases.*

A more precise signal of future loan performance reduces the loan officer's incentive to lie. He profits less from falsely claiming that his soft-information is positive, since he is less likely to receive the bonus. An increase in ψ reduces the probability $\Pr[\overline{\theta}|\underline{s},\overline{h}]$ which allows the bank to set a higher ratio of pay $\frac{\overline{w}_r}{\underline{w}_r}$.

One possibility for the bank to increase the precision of r and hence to relax the agency problem under soft-information lending is to invest in a more thorough loan review process. Udell (1989) provides evidence that banks invest more in monitoring loans when they delegate more authority to loan officers, i.e., when one would expect the agency problem to be larger. Banks with a more thorough loan review process provide steeper compensation schemes to loan officers ($\frac{\overline{w}_r}{\underline{w}_r}$) under soft-information lending and are less likely to switch to hard-information lending when competition intensifies.

Another possibility to increase the precision of the loan performance signal is to shorten the maturity of loans.[13] In this case, banks that extend more short-term loans have steeper compensation schemes under soft-information lending and are more likely to maintain the use of soft-information as competition intensifies.

5 Excessive Lending

According to Corollary 2, our model predicts that as competition tilts the bank's choice towards hard-information lending, average loan quality decreases. It may be argued that this observation depends on the discrete change in the bank's lending practice around the competition threshold $\lambda_E = \widehat{\lambda}_E$. We now extend the model to show that this is not the case. At the cost of complicating notation and the exposition of results, we introduce a continuous signal for the loan officer's soft information. This allows to study a gradual effect of competition on the bank's lending behavior.

Extending the Model Allowing for a continuous soft-information signal $s \in [\underline{s}, \overline{s}]$, we denote the conditional probability of a high-type borrower by $\Pr[\overline{\theta}|s, h]$ and stipulate that it is strictly increasing in s and is strictly higher when $h = \overline{h}$. We also maintain that the bank can lend profitably when both hard and soft information are highest, i.e., when $\Pr[\overline{\theta}|\overline{s}, \overline{h}] > \mu^*$, while the expected NPV from a loan is negative when hard and soft information (maximally) disagree, $(\underline{s}, \overline{h})$ and $(\overline{s}, \underline{h})$ (a fortiori, the NPV is negative at $(\underline{s}, \underline{h})$). In terms of first principles, we may stipulate that s is obtained from some signal-generating distribution $F(s|\theta)$, where $F(s|\overline{\theta})$ dominates $F(s|\underline{\theta})$ in the sense of the Monotone Likelihood Ratio Property and where $f(s|\theta) > 0$ everywhere. This ensures the strict monotonicity of $\Pr[\overline{\theta}|s, h]$ in s. As s and h are still independently drawn, we have

$$\Pr[\overline{\theta}|s, h] = \frac{\mu_0 f(s|\overline{\theta})\rho_H}{\mu_0 f(s|\overline{\theta})\rho_H + (1-\mu_0) f(s|\underline{\theta})(1-\rho_H)}. \tag{35}$$

The characterization is analogous to the case with discrete signals. By optimality, a loan application will still be rejected when $h = \underline{h}$. When the bank does not use soft information, we can apply our previous analysis of hard-information lending. We characterize next the outcome when the bank uses soft information.

Compensation with Soft Information Under soft-information lending, the loan-approval decision now describes a subset of $[\underline{s}, \overline{s}]$ for which the loan is approved. As before, the cheapest way to provide incentive compatible pay is to have a bonus when the borrowers succeeds: $w(s, \overline{h}; \overline{R}) > w(s, h; 0) = 0$. Moreover, the bonus is independent of soft information, $w(s, \overline{h}; \overline{R}) = \overline{w}$ for all s, since there is nothing to be gained from soft information once it has been revealed and the loan has been approved. As before, there can be a wage $\underline{w}$ when no loan was made. Given the strict monotonicity of $\Pr[\overline{\theta}|s, h]$ in s, the truth-telling constraints IC_T translate into an indifference condition: a loan is approved when soft information is favorable enough, $s \geq s^*$, where at the "cutoff signal" s^* we have

$$\Pr[\overline{\theta}|s^*, \overline{h}]p\overline{w} = \underline{w}. \tag{36}$$

At the "cutoff signal" $s = s^*$, the loan officer is indifferent between the approval and rejection of a loan.

The incentive constraint IC_e to elicit prospecting effort e^* becomes

$$\int_{s^*}^{\overline{s}} \left[\Pr[\overline{\theta}|s, \overline{h}]p\overline{w} - \underline{w}\right] g(s|\overline{h})ds = \frac{c'(e^*)}{q'(e^*)}, \tag{37}$$

where we have used $g(s|\overline{h}) = \mu_0 f(s|\overline{\theta})\rho_H + (1-\mu_0)f(s|\underline{\theta})(1-\rho_H)$ to abbreviate the notation. As before, to induce effort, the wedge between the expected compensation when a loan is approved and $\underline{w}$ must be sufficiently large. From the two incentive constraints (36) and (37), we obtain the characterization of the loan officer's compensation

$$\overline{w} = \left[\frac{c'(e^*)}{q'(e^*)}\right] \frac{1}{p} \frac{1}{\int_{s^*}^{\overline{s}} \left(\Pr[\overline{\theta}|s, \overline{h}] - \Pr[\overline{\theta}|s^*, \overline{h}]\right) g(s|\overline{h})ds} \tag{38}$$

$$\underline{w} = \left[\frac{c'(e^*)}{q'(e^*)}\right] \frac{\Pr[\overline{\theta}|s^*, \overline{h}]}{\int_{s^*}^{\overline{s}} \left(\Pr[\overline{\theta}|s, \overline{h}] - \Pr[\overline{\theta}|s^*, \overline{h}]\right) g(s|\overline{h})ds} \tag{39}$$

and the bank's compensation cost under soft-information lending

$$K_S(e^*, s^*) = \left[\frac{c'(e^*)}{q'(e^*)}\right] \left[q(e^*) + \frac{\Pr[\overline{\theta}|s^*, \overline{h}]}{\int_{s^*}^{\overline{s}} \left(\Pr[\overline{\theta}|s, \overline{h}] - \Pr[\overline{\theta}|s^*, \overline{h}]\right) g(s|\overline{h}) ds}\right]. \tag{40}$$

That is, $K_S(e^*, s^*)$ captures the bank's compensation cost when it induces prospecting effort e^* *and* a loan-approval cutoff s^*. The expression is analogous to the one with a discrete signal for soft information, except that: i) the loan officer is now indifferent between loan approval and rejection when $s = s^*$, whereas before he was indifferent when $s = \underline{s}$, and ii) to obtain the loan officer's expected compensation when a loan is approved we now have to take the expecation over realizations $s > s^*$, instead of taking only the realization $s = \overline{s}$.

Loan Approval with Soft Information Compared to the case with a discrete soft-information signal, the bank now has one more choice variable: the cutoff s^*. For a given prospecting effort e^*, the bank's optimal choice of s^* maximizes its profits

$$\Pi(e^*, s^*) = q(e^*) \int_{s^*}^{\overline{s}} \left[pR^s \Pr[\overline{\theta}|s, \overline{h}] - k\right] g(s|\overline{h}) ds - K_S(e^*, s^*). \tag{41}$$

In what follows, we assume that the optimization problem is strictly concave. When $s^* > \underline{s}$ so that soft information is indeed used, the optimal cutoff s^* solves the first-order condition

$$-q(e^*) \left[pR^s \Pr[\overline{\theta}|s^*, \overline{h}] - k\right] g(s^*|\overline{h}) = \frac{\partial}{\partial s^*} K_S(e^*, s^*). \tag{42}$$

The right-hand side of the condition is strictly negative: The bank's compensation cost under soft-information lending increases in the cutoff s^*.[14] The intuition follows, as before, from a more difficult balance between the loan officer's truth-telling and prospecting incentives. Since a higher cutoff s^* makes loan approval less likely, the bank must increase the loan performance bonus $\overline{w}$ in order to maintain a prospecting effort e^*. A higher bonus, however, increases the loan officer's incentive to lie about soft-information in order to increase the chances of loan approval. To restore his incentive for truth-telling, the bank must increase the base wage $\underline{w}$ and pay him more when a loan is rejected, which in turn hurts his incentive to prospect. From the strict monotonicity of $\Pr[\overline{\theta}|s, h]$ in s, we see that the ratio of the loan officer's performance pay to his base wage

$$\frac{\overline{w}}{\underline{w}} = \frac{1}{\Pr[\overline{\theta}|s^*, \overline{h}]p} \tag{43}$$

must decrease when the bank wants to implement a stricter loan-approval rule (higher cutoff s^*).

Since $K_S(e^*, s^*)$ strictly increases in s^*, the first-order condition (42) for the optimal choice of the cutoff s^* implies that the bank expects to make a loss from the *marginal* loan (at $s = s^*$): $pR^s \Pr[\overline{\theta}|s^*, \overline{h}] < k$. That is, when we define a cutoff $\underline{s} < s_{NPV} < \overline{s}$, so that

$$pR^s \Pr[\overline{\theta}|s_{NPV}, \overline{h}] = k, \tag{44}$$

then $s^* < s_{NPV}$. We can therefore state the following results.

Proposition 5 *Suppose soft-information is given by a continuous signal. When the bank wants to use soft information, a loan is approved when hard information is positive $h = \overline{h}$ and soft information is above a cutoff s^*, $s \geq s^*$. The loan officer's optimal compensation is given by a base wage (paid when no loan is made) $\underline{w}$ and a bonus (paid when an approved loan performs) $\overline{w}$, as given by (39) and (38), respectively. It is optimal for the bank to implement a cutoff s^* so that the marginal loan at $s = s^*$ is loss-making in expectations: $s^* < s_{NPV}$. The bank does not use soft information when $s^* \leq \underline{s}$.*

The optimal cutoff $s^* < s_{NPV}$ implies that the bank expects to make losses on some loans even though it takes into account all available information, including the loan officer's soft information. For the bank this is optimal since lowering its lending standard s^* relaxes the agency problem and reduces the cost of compensation. We show next how competition affects such "excessive lending".

Competition When the soft information signal was binary, we found that the *difference* between the compensation cost under soft- and hard-information lending was larger when the bank implemented a higher prospecting effort in response to more competition, which lead to a switch to hard-information lending. This is still the case now and it implies that soft information will not be used at all when competition is sufficiently intense. For ease of exposition, however, we have not included this case in the following Proposition and instead focus on the effect of competition on the bank's lending standard with soft-information.

Proposition 6 *Suppose soft-information is given by a continuous signal. As long as soft information is still used when competition intensifies (higher λ_E), the lending standard s^* strictly decreases as λ_E increases. It then becomes less likely that bad loans are screened out based on soft information.*

Proof. See Appendix.

As competition intensifies, average loan quality decreases. The bank makes less use of soft information, thereby pushing down s^*. This is optimal for the bank even though more loans are made with a negative NPV since it can induce a higher prospecting effort at a lower compensation cost.

6 Competition in Loan Rates

The main novelty of our model is the introduction of loan prospecting as a strategic variable for banks. Whereas the literature typically views as borrowers as active shoppers for low loan rates among banks, we viewed borrowers as more passive in order to capture the role of prospecting, through which a bank protects its market share from competition. In this section, we extend our model to also allow for competition in loan rates. We first allow rival banks to compete both by prospecting and loan rates. Then, we allow the incumbent bank to respond to competitive pressures by adjusting its loan rate in addition to its prospecting effort.

Extending the Model. We now stipulate that the probability with which the borrower is interested in applying for a loan from the incumbent bank at $\tau = 1$, the time when he is contacted first by the incumbent bank's loan officer, depends negatively to offered loan rate R^s and is given by $Q_M(R^s)$, which is continuously differentiable with $\partial Q_M/\partial R^s < 0$ (previously we had $Q_M = 1$). The subscript indicates that the incumbent bank acts as a monopolist at $\tau = 1$ since its market is not yet contested by rivals. When the potential borrower has not received a loan at $\tau = 1$, which happens with probability $1 - \lambda_I(e)Q_M$, he subsequently prospected, as before, by a rival bank at $\tau = 2$ with probability λ_E. In that case, we now stipulate that the borrower nevertheless applies for a loan at the incumbent bank with probability $Q_C(R^s, R^s_E)$, where R^s_E denotes the loan rate offered by the entrant (previously we had $Q_C = 0$). This probability is continuously differentiable with $\partial Q_C/\partial R^s < 0$ and $\partial Q_C/\partial R^s_E > 0$. The subscript now indicates that the incumbent is competing with the entrant. The probabilities Q_M and Q_C play the role of standard demand functions (we also assume that $Q_C(R^s, R^s_E) \leq Q_M(R^s)$, and strictly so when R^s_E is not too high). As before, should the borrower not been prospected either by the incumbent or a rival at $\tau = 1$ or $\tau = 2$, then he eventually becomes aware of his need for a loan at turns to the local, incumbent bank at $\tau = 3$. With the linear specification $\lambda_I(e) = e$ (equation (22)), the incumbent bank's probability of receiving a loan application (its "loan demand") is now given by

$$q(e, R^s, \lambda_E, R^s_E) = Q_M(R^s) - (1 - e)\lambda_E \Delta_Q(R^s, R^s_E), \tag{45}$$

where $\Delta_Q(R^s, R^s_E) = Q_M(R^s) - Q_C(R^s, R^s_E)$.

Extending our model in this way deserves two comments. First, the incumbent bank cannot price discriminate between the potential borrower at $\tau = 1$ (when he is not yet "aware" of a later, alternative offer by a rival bank) and the potential borrower at $\tau = 2$ (when is aware).[15] Second, the composition of the pool of borrowers that the incumbent bank faces is independent of its own and, in particular, its rival's loan rate. Hence, the incumbent does not face an "adverse selection" problem.

Reaction to Loan Rate Competition. We first consider the incumbent bank's reaction to more intense competition in terms of the optimal prospecting effort it induces and its choice of the lending regime. Holding the loan rate it charges R^s constant, we can compare the impact of rivals' loan rate competition (lowering R^s_E) to our previous case where rivals competed by increasing their prospecting (higher λ_E). Our results still hold: Competition (in loan rates) induces the incumbent bank to elicit a higher prospecting effort from its loan officer and it makes it more likely to switch from soft- to hard-information lending. The intuition is as before: more intense competition (lower R^s_E) shifts the incumbent bank's demand for loans down ($\partial q/\partial R^s_E > 0$) and it makes his its demand more responsive to prospecting:

$$\frac{\partial^2 q}{\partial e \partial R^s_E} = -\lambda_E \frac{\partial Q_C}{\partial R^s_E} < 0. \tag{46}$$

In response to more intense price competition, the incumbent optimally shields itself by inducing a higher prospecting effort from its loan officer (we show this formally in the proof of Proposition 7). While this is clearly an implication of how we model prospecting, it seems natural that the bank responds in the same way either to loan rate or loan prospecting competition:

Proposition 7 *Suppose competition intensifies as entrants charge a lower loan rate (lower R^s_E), while the incumbent bank reacts only through adjusting the loan officer's prospecting* *incentives and, potentially, its use of soft information. Then, the following holds:*

i) As loan-rate competition intensifies, the bank optimally induces more prospecting effort.

ii) Provided that both lending regimes arise for values of R_E^s, there exists a cutoff $\widehat{R}_E^s$ such that soft-information lending is chosen when competition is low ($R_E^s > \widehat{R}_E^s$), while hard-information lending is chosen when competition is high ($R_E^s < \widehat{R}_E^s$).

Proof. See Appendix.

Loan Rate Policy. So far, we held the incumbent bank's loan rate constant and focused on its reaction to competition in terms of prospecting effort and choice of lending regime. We now discuss how the analysis changes when the bank can also adjust its loan rate R^s.

As stipulated above, loan demand Q_M and Q_C should be decreasing in R^s. However, there is no clear presumption of how the difference $\Delta_Q = Q_M - Q_C$ should change in R^s. When demand is linear in prices (loan rates), then the cross-price effects are zero, so that $d^2Q_C/(dR^s dR_E^s) = 0$ and $d^2\Delta_Q/(dR^s dR_E^s) = 0$. While the case of linear demand is specific, it illustrates that one should perhaps not have strong views about the sign of this relationship. Hence, we assume that $d^2\Delta_Q/(dR_E^s dR^s) = 0$. We then establish in Appendix B that

$$\frac{d^2\Pi_H^*}{dR^s dR_E^s} > 0, \tag{47}$$

which means that in the case of hard-information lending, as in standard models of price competition, the incumbent bank's and its rivals' loan rates are strategic complements: The incumbent bank has a stronger incentive to reduce its loan rate when its rivals' loan rate is lower. The same holds with respect to the rivals' other strategy variable, namely their prospecting effort:

$$\frac{d^2\Pi_H^*}{dR^s d\lambda_E} < 0. \tag{48}$$

The incumbent bank has a stronger incentive to reduce its loan rate when rivals prospect more for borrowers (high λ_E). The intuition for (48) is similar to that for the more standard strategic complementarity in prices in (47). The incumbent bank trades off the benefit of a cut in its loan rate, i.e., higher loan volume, with the cost, i.e., less profits on made loans. When loan demand drops due more intense competition (either because of lower rates or because of high prospecting of rivals), the cost decreases and it becomes more attractive to cut the loan rate R^s.

From our previous analysis, we also have

$$\frac{d^2\Pi_H^*}{de^* d\lambda_E} > 0 \text{ and } \frac{d^2\Pi_H^*}{de^* dR_E^s} < 0, \tag{49}$$

that is, the incumbent induces a higher prospecting effort irrespective of whether competition in loan rates or in prospecting intensifies. The cross-derivatives in (47), (48), and (49) show that our model yields an intuitive result: the incumbent bank becomes more aggressive when competition intensifies. While we have analyzed only the case of hard-information lending so far, we show in Appendix B that the same conclusion holds for soft-information lending.

Moreover, we establish in Appendix B that

$$\frac{d^2\Pi_H^*}{dR^s de^*} > 0. \tag{50}$$

Ceteris paribus, the bank wants to implement a lower prospecting effort when it lowers its loan rate (and vice versa). Again, this is intuitive since the bank has a lower incentive to induce costly a prospecting effort when it earns less from a given loan. The positive cross-derivative in (50) now implies that when the bank becomes more aggressive in response to more competition, it is not clear whether this results in both a lower loan rate *and* a higher prospecting effort, even though our previous, partial analysis suggests this.

In sum, while our analysis suggests that the bank reacts to more competition by providing steeper incentives to increase the prospecting effort of its loan officer, which makes soft-information lending less attractive, there is a counter-veiling effect when the bank also cuts its loan rate. The relevance of the identified prospecting channel through which competition affects compensation as well as the use of soft information and, thereby, the bank's lending standard is therefore an empirical question.

7 Concluding Remarks

We propose a model of bank lending in which loan officers must exert costly effort to prospect for new lending opportunities. We embed the contracting model into a simple framework of competition that makes loan prospecting valuable in the first place. A bank's demand for loans becomes more elastic with respect to its loan officer's prospecting effort when competition intensifies. The positive relationship between competition and the elasticity of demand is analogous to the effect of competition on price elasticity in standard models of Industrial Organization.

In addition to prospecting for loans, a loan officer can also have the task of communicating the soft information that he acquired in the process of prospecting. Part of the bank's competitive strategy is to determine to what extent it should use the loan officer's soft information to screen out bad borrowers. When the bank decides to disregard soft information and to rely only on hard information, its loan officer becomes a salesperson: he is optimally paid only on the basis of the volume of loans he generated. When, instead, the bank uses soft information in its loan approval, the loan officer performs two tasks, prospecting and communicating soft information. In that case, his compensation scheme is flatter (it comprises a base wage when no loan is made) and performance based (it comprises a bonus when a made loan performs).

A central part of our analysis is that as competition intensifies, the bank finds it optimal to induce a higher prospecting effort. But this makes eliciting soft information more costly. More competition and higher prospecting effort may thus go hand-in-hand with a less intensive use of soft information and a lower lending standard, which in turn pushes up loan volume. At the same time, the loan officer's compensation becomes steeper, linked to loan volume and independent of future loan performance.

The finding that loan approval is more likely to condition on hard information (e.g., credit scores) as competition intensifies, provides a novel perspective. It contrasts with the view that the adoption of credit scoring by rivals itself leads to more intense competition. Taken together, this suggests a complementarity between competition and the adoption of credit scoring, whose mutually reinforcing developments may help to explain cross-country differences.

References

Agarwal, S. and Wang, F.H., 2009, Perverse incentives at the banks? Evidence from a natural experiment, Federal Reserve Bank of Chicago WP 09/08.

Banerjee, A., Cole, S. and Duflo, E., 2009, Default and punishment: Incentives and lending behavior in Indian banks, mimeo, Havard Business School.

Berger, A.N., Cowen, A.M. and Frame, W.S., 2011, The surprising use of credit scoring in small business lending by community banks and the attendant effects on credit availability, risk, and profitability, Journal of Financial Services Research 39, 1-17.

Berger, A.N., Frame, W.S. and Miller, N.H., 2005, Credit scoring and the availability, price, and risk of small business credit, Journal of Money, Credit and Banking 37, 191-222.

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

Berger, A.N. and Udell, G., 2002, Small business credit availability and relationship lending: The importance of bank organizational structure, Economic Journal 112, F32-F53.

Berger, A.N. and Udell, G., 2004, The institutional memory hypothesis and the procyclicality of bank lending behavior, Journal of Financial Intermediation 13, 458-495.

Bofondi, M. and Gobbi, G., 2006, Informational barrier to entry into credit markets, Review of Finance 10, 39-67.

Broecker, T., 1990, Credit-worthiness tests and interbank competition, Econometrica 58, 429-52.

Cole, S., Kanz, M. and Klapper, L., 2010, Rewarding calculated risk-taking: Evidence from a series of experiments with commercial bank loan officers, mimeo, Harvard Business School.

Dell'Ariccia, G., Friedman, E. and Marquez, R., 1999, Adverse selection as a barrier to entry in the banking industry, RAND Journal of Economici 30, 515-534.

Dell'Ariccia, G., and Marquez, R., 2006, Lending booms and lending standards, Journal of Finance 61, 2511-2546.

Dewatripont, M. and Tirole, J., 1999, Advocates, Journal of Political Economy 107, 1-39.

Frank, M., 2011, Bank loan search, mimeo, University of Minnesota.

Freixas, X. and Rochet, J.-C., 2008, Microeconomics of banking, MIT Press.

Gromb, D. and Martimort, D., 2007, Collusion and the organization of delegated expertise, Journal of Economic Theory 137, 271-299.

Hauswald, R. and Marquez, R., 2003, Information technology and financial services competition, Review of Financial Studies 16, 921-48.

Hauswald, R. and R. Marquez, 2006, Competition and strategic information acquisition in credit markets, Review of Financial Studies 19, 967-1000.

Hertzberg, A., Liberti, J.M. and Paravisini, D., 2010, Information and incentives inside the firm: Evidence from loan officers' turnover, Journal of Finance 65, 795-828.

Holmström, B. and Milgrom, P., 1991, Multitask principal-agent analysis: Incentive contracts, asset ownership and job design, Journal of Law, Economics and Organization 7, 24-52.

Inderst, R. and Müller, H., 2006, Informed lending and security design, Journal of Finance 61, 2137-62.

Inderst, R. and Ottaviani, M., 2009, Misselling through agents, American Economic Review 99, 883-908.

Inderst, R. and Pfeil, S., 2009, Compensation and securitization, mimeo, University of Frankfurt.

James, C. and Houston, J., 1996, Evolution or extinction: Where are banks headed?, Journal of Applied Corporate Finance 9, 8-23.

Lambert, R., 1986, Executive effort and selection of risky projects, RAND Journal of Economics 17, 77-88.

Levitt, D. and C. Snyder, 1997, Is no news bad news? Information transmission and the role of "early warning" in the principal-agent model, RAND Journal of Economics 28, 641-661.

Liberti, J. and Mian, A., 2009, Estimating the effect of hierarchies on information use, Review of Financial Studies 22, 4057-4090.

Loranth, G. and Morrison, A., 2010, Internal reporting systems, compensation contracts, and bank regulation, CEPR Discussion Paper 7179.

Malcomson, J., 2009, Principal and expert agent, B.E. Journal of Theoretical Economics 9, Article 17.

Petersen, M. and Rajan, R., 2002, Does distance still matter? The information revolution in small business lending, Journal of Finance 57, 2533–2570.

Puri, M., Rocholl, J. and Steffen, S., 2010, On the Importance of Prior Relationships in Bank Loans to Retail Customers, mimeo, Duke University.

Rajan, R., 1994, Why bank credit policies fluctuate: A theory and some evidence, Quarterly Journal of Economics 109, 399-411.

Ross, D., 2011, On evaluation costs in strategic factor markets: the implications for competition and organizational design, Management Science, forthcoming.

Ruckes, M., 2004, Bank competition and credit standards, Review of Financial Studies 17, 1073-1102.

Stein, J., 2002, Information production and capital allocation: Decentralized versus hierarchical firms, Journal of Finance 57, 1891-1921.

Stiroh, K. and P. Strahan, 2003, Competitive dynamics of deregulation: Evidence from U.S. banking, Journal of Money, Credit and Banking 35, 801-828.

Treacey, W.F. and Carey, M.S., 1998, Credit risk rating at large US banks, Federal Reserve Bulletin, 897-921.

Udell, G., 1989, Loan quality, commercial loan review and loan officer contracting, Journal of Banking and Finance 13, 367-82.

Appendix A: Proofs

Proof of Proposition 2. The bank's optimization problem is:

$$\min_{w(\overline{s},\overline{h};R^s),w(\overline{s},\overline{h};0),\underline{w}} \quad q(e^*)\Pr[\overline{s},\overline{h}]\left[\Pr[\overline{\theta}|\overline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)+(1-\Pr[\overline{\theta}|\overline{s},\overline{h}]p)w(\overline{s},\overline{h};0)\right]$$
$$+\left[1-q(e)\Pr[\overline{s},\overline{h}]\right]\underline{w}$$

$$\begin{aligned}
\text{subject to} \quad & \Pr[\overline{\theta}|\overline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)+(1-\Pr[\overline{\theta}|\overline{s},\overline{h}]p)w(\overline{s},\overline{h};0)\geq\underline{w} && [\nu_1]\\
& \Pr[\overline{\theta}|\underline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)+(1-\Pr[\overline{\theta}|\underline{s},\overline{h}]p)w(\overline{s},\overline{h};0)\leq\underline{w} && [\nu_2]\\
& w(\overline{s},\overline{h};R^s)\geq 0 && [\nu_3]\\
& w(\overline{s},\overline{h};0)\geq 0 && [\nu_4]\\
& \underline{w}\geq 0 && [\nu_5]
\end{aligned}$$

and the loan officer's incentive constraint IC_e (equation (13)). The corresponding Lagrange multipliers are in square brackets. The first-order conditions with respect to $w(\overline{s},\overline{h};R^s)$, $w(\overline{s},\overline{h};0)$ and $\underline{w}$ are after some manipulation:

$$\begin{aligned}
-q(e^*)\Pr[\overline{s},\overline{h}]+\nu_1-\nu_2\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]}+\hat{\nu}_3 &= 0 && (51)\\
-q(e^*)\Pr[\overline{s},\overline{h}]+\nu_1-\nu_2\frac{1-\Pr[\overline{\theta}|\underline{s},\overline{h}]p}{1-\Pr[\overline{\theta}|\overline{s},\overline{h}]p}+\hat{\nu}_4 &= 0 && (52)\\
1-q(e^*)\Pr[\overline{s},\overline{h}]+\nu_1-\nu_2-\nu_5 &= 0, && (53)
\end{aligned}$$

where $\hat{\nu}_3=\frac{\nu_3}{\Pr[\overline{\theta}|\overline{s},\overline{h}]p}$ and $\hat{\nu}_4=\frac{\nu_4}{1-\Pr[\overline{\theta}|\overline{s},\overline{h}]p}$. Since $\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]}<1$ and $\frac{1-\Pr[\overline{\theta}|\underline{s},\overline{h}]p}{1-\Pr[\overline{\theta}|\overline{s},\overline{h}]p}>1$, equations (51) and (52) imply that $\hat{\nu}_4>\hat{\nu}_3\geq 0$. Hence, $w(\overline{s},\overline{h};0)=0$. We also have $\nu_2>0$. Suppose that not. Then (51) and (52) imply $\hat{\nu}_4=\hat{\nu}_3$, a contradiction to the previous result. Hence, $\Pr[\overline{\theta}|\underline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)=\underline{w}$. Substituting these results into the incentive constraint IC_e (equation (13)) yields

$$\Pr[\overline{s},\overline{h}]\left[\Pr[\overline{\theta}|\overline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)-\Pr[\overline{\theta}|\underline{s},\overline{h}]pw(\overline{s},\overline{h};R^s)\right]=\frac{c'(e^*)}{q'(e^*)}, \tag{54}$$

which simplifies to the expression for $w(\overline{s},\overline{h};R^s)$ in the Proposition.

Proof of Lemma 1. When there is an interior solution, which we denote by e_H^*, it satisfies the first-order condition

$$q'(e_H^*)\sum_{(s,h)\in A_H}\Pr[s,h]\left(\Pr[\overline{\theta}|s,h]pR^s-k\right)=\frac{d}{de_H^*}\left(\frac{c'(e_H^*)}{q'(e_H^*)}q(e_H^*)\right), \tag{55}$$

or after substituting for $q(\cdot)$ from (20),

$$\lambda_E\lambda_I'(e_H^*)\sum_{(s,h)\in A_H}\Pr[s,h]\left(\Pr[\overline{\theta}|s,h]pR^s-k\right)=\frac{d}{de_H^*}\left(\frac{c'(e_H^*)}{\lambda_I'(e_H^*)}\left[\frac{1-\lambda_E}{\lambda_E}+\lambda_I(e_H^*)\right]\right). \tag{56}$$

With the linear-quadratic specification (22), this becomes the expression in the Lemma.

Proof of Lemma 2. When there is an interior solution, which we denote by e_S^*, it satisfies the first-order condition

$$\begin{aligned}&q'(e_S^*)\Pr[\overline{s},\overline{h}]\left(\Pr[\overline{\theta}|\overline{s},\overline{h}]pR^s-k\right)\\ =\ &\frac{d}{de_S^*}\left(\frac{c'(e_{SH}^*)}{q'(e_{SH}^*)}\left[q(e_S^*)+\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}\right]\right),\end{aligned}$$

or, after substituting for $q(\cdot)$ from (20),

$$\begin{aligned}&\lambda_E\lambda_I'(e_S^*)\Pr[\overline{s},\overline{h}]\left[\Pr[\overline{\theta}|\overline{s},\overline{h}]pR^s-k\right]\\ =\ &\frac{d}{de_S^*}\left(\frac{c'(e_S^*)}{\lambda_I'(e_S^*)}\left[\frac{1-\lambda_E}{\lambda_E}+\lambda_I(e_S^*)+\frac{1}{\lambda_E}\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}\right]\right).\end{aligned} \tag{57}$$

With the linear-quadratic specification (22), this becomes the expression in the Lemma.

Proof of Proposition 3. We first show that we can indeed restrict ourselves to $A = \{(\overline{s}, \overline{h})\}$ or $A = \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}$. Since we stipulated that $\Pr[\overline{\theta}|\overline{s}, \overline{h}] > \mu^*$, the bank can lend profitably when both hard and soft information are positive. Since hard information is verifiable, the bank can use it without additional costs. Recall also that the loan's NPV is negative when soft and hard information disagree. Thus, when the bank does not make use soft information, the bank optimally chooses $A = \{(\overline{s}, \overline{h}), (\underline{s}, \overline{h})\}$, rejecting an applicant if and only if $h = \underline{h}$. Finally, when the bank incurs the cost of eliciting (negative) soft information, it optimally will exclude applicants who have either negative soft or negative hard information. (As hard information is verifiable, it is immediate to show that excluding loans with negative hard information does not increase the loan officer's rent.)

Denote the profits at the respective optimal effort levels by Π_S^* and Π_H^*: $\Pi_S^* = \Pi_S(e_S^*)$ and $\Pi_H^* = \Pi_H(e_H^*)$. When we compare these two profit levels as the intensity of competition λ_E changes, we limit ourselves for brevity's sake to the case when the optimal effort levels e_S^* and e_H^* are interior (it is straightforward to extend the comparison to corner solutions).

To show that the bank switches from soft- to hard-information lending as competition increases beyond a threshold level $\hat{\lambda}_E$, we show that whenever $\Pi_H^*(\lambda_E) = \Pi_S^*(\lambda_E)$ then at that λ_E we must have

$$\frac{d\Pi_H^*}{d\lambda_E} > \frac{d\Pi_S^*}{d\lambda_E}. \tag{58}$$

Substituting e_S^* and e_H^* from Lemma 1 and 2 into (24) and (29) yields

$$\begin{aligned}
\Pi_H^*(\lambda_E) &= \frac{q^2(e_H^*)}{\gamma\lambda_E^2}, \\
\Pi_S^*(\lambda_E) &= \frac{q^2(e_S^*)}{\gamma\lambda_E^2} + \frac{1-\lambda_E}{\gamma\lambda_E^2}\frac{1}{\Pr[\overline{s}, \overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}]}.
\end{aligned}$$

The condition $\Pi_H^*(\lambda_E) = \Pi_S^*(\lambda_E)$ then becomes

$$q^2(e_H^*) - q^2(e_S^*) = (1-\lambda_E)\frac{1}{\Pr[\overline{s}, \overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s}, \overline{h}]}{\Pr[\overline{\theta}|\overline{s}, \overline{h}] - \Pr[\overline{\theta}|\underline{s}, \overline{h}]} > 0. \tag{59}$$

This implies that $e_H^* > e_S^*$ must hold when competition is such that bank profits from soft- and hard-information lending are equal.

From the envelope theorem, we have next that

$$\begin{aligned}
\frac{d\Pi_H^*}{d\lambda_E} &= -\frac{2}{\lambda_E}\Pi_H^*(\lambda_E) - \frac{1}{\gamma\lambda_E^2}2q(e_H^*)(1-e_H^*), \\
\frac{d\Pi_S^*}{d\lambda_E} &= -\frac{2}{\lambda_E}\Pi_S^*(\lambda_E) - \frac{1}{\gamma\lambda_E^2}\left[2q(e_S^*)(1-e_S^*) + \frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]}\right].
\end{aligned}$$

Hence, for (58) to hold when $\Pi_H^*(\lambda_E) = \Pi_S^*(\lambda_E)$, it must be that

$$q(e_S^*)(1-e_S^*) - q(e_H^*)(1-e_H^*) + \frac{1}{2}\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]} > 0. \tag{60}$$

After substituting $1 - e = [1 - q(e)]/\lambda_E$ (obtained from (20) and (22)), the condition becomes

$$q(e_S^*)(1-q(e_S^*)) - q(e_H^*)(1-q(e_H^*)) + \frac{\lambda_E}{2}\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]} > 0. \tag{61}$$

Using (59) to substitute for $q^2(e_H^*) - q^2(e_S^*)$ and using $q(e_S^*) - q(e_H^*) = \lambda_E(e_S^* - e_H^*)$, this further transforms to

$$2\lambda_E(e_S^* - e_H^*) + (2-\lambda_E)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]} > 0. \tag{62}$$

We next substitute the expressions for e_S^* and e_H^* from Lemma 1 and 2. To save on notation, we write

$$\pi_H = \sum_{(s,h)\in A_H} \Pr[s,h]\left(\Pr[\overline{\theta}|s,h]pR^s - k\right) \text{ and } \pi_S = \Pr[\overline{s},\overline{h}]\left(\Pr[\overline{\theta}|\overline{s},\overline{h}]pR^s - k\right), \tag{63}$$

where $\pi_S > \pi_H$. Then, (62) becomes

$$\gamma\lambda_E^2\left(\pi_S-\pi_H\right)+(1-\lambda_E)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}>0, \tag{64}$$

which always holds. Hence, the difference $\Pi_H^*(\lambda_E)-\Pi_S^*(\lambda_E)$ changes sign at most once and if it does, then there exists a threshold level of competition $\hat{\lambda}_E$ so that $\Pi_H^*(\lambda_E)>\Pi_S^*(\lambda_E)$ for $\lambda_E>\hat{\lambda}_E$ and $\Pi_H^*(\lambda_E)<\Pi_S^*(\lambda_E)$ for $\lambda_E<\hat{\lambda}_E$.

Proof of Corollary 2. With respect to assertion i), the monotonic relationship between e^* and λ_E under either lending regime follows from the respective results in Lemmas 1 and 2. That $e_H^*>e_S^*$ holds strictly for $\lambda_E=\widehat{\lambda}_E$ follows from expression (59) in the proof of Proposition 3. Assertion ii) is immediate.

Finally, turning to assertion iii), the comparative statics of W follow from $dW/de^*>0$ (cf. Proposition 1) together with $de_H^*/d\lambda_E>0$, where strictly positive (cf. Lemma 1). With respect to compensation under soft-information lending, recall first that $de_S^*/d\lambda_E>0$, where strictly positive (cf. Lemma 2). Next, that $\overline{w}-\underline{w}$ strictly increases in the implemented effort follows as, given expression (17), $\overline{w}/\underline{w}>1$ stays constant with $d\overline{w}/de^*>0$.

Proof of Proposition 6. When soft information is still used, so that from Proposition 5 there is a cutoff $s^*>\underline{s}$, then by assumed strict concavity of the bank's program the respective choices s^* and e^* are characterized by two first-order conditions. While that for s^* was already derived in (42), we obtain for e^* the respective condition

$$q'(e^*)\int_{s^*}^{\overline{s}}\left[pR^s\Pr[\overline{\theta}|s,\overline{h}]-k\right]g(s,\overline{h})ds=\frac{\partial}{\partial e^*}K_S(e^*,s^*). \tag{65}$$

Further, after substitution for $q(e)$ and $c(e)$, we have that

$$\begin{aligned}\frac{\partial\Pi_S^2}{\partial e^*\partial s^*} &= -\lambda_E\left[pR^s\Pr[\overline{\theta}|s^*,\overline{h}]-k\right]g(s^*,\overline{h})\\ &\quad -\frac{1}{\gamma\lambda_E}\frac{\partial}{\partial s^*}\left[\frac{\Pr[\overline{\theta}|s^*,\overline{h}]}{\int_{s^*}^{\overline{s}}\left[\Pr[\overline{\theta}|s,\overline{h}]-\Pr[\overline{\theta}|s^*,\overline{h}]\right]g(s,\overline{h})ds}\right].\end{aligned}$$

When we evaluate this at the optimal level of s^*, using (42), we obtain

$$\frac{\partial \Pi_S^2}{\partial e^* \partial s^*} = \left[pR^s \Pr[\overline{\theta}|s^*, \overline{h}] - k \right] g(s^*, \overline{h}) \frac{1}{e^*}(1 - \lambda_E) < 0, \tag{66}$$

where the strict inequality follows from Proposition 5. Next, note that

$$\begin{aligned} \frac{\partial \Pi_S^2}{\partial e^* \partial \lambda_E} &= \int_{s^*}^{\overline{s}} \left[pR^s \Pr[\overline{\theta}|s, \overline{h}] - k \right] g(s, \overline{h}) ds \\ &\quad + \frac{1 - \lambda_E}{\gamma \lambda_E^2} + \frac{1}{\gamma \lambda_E^2} \left[\frac{\Pr[\overline{\theta}|s^*, \overline{h}]}{\int_{s^*}^{\overline{s}} \left[\Pr[\overline{\theta}|s, \overline{h}] - \Pr[\overline{\theta}|s^*, \overline{h}] \right] g(s, \overline{h}) ds} \right] \\ &> 0. \end{aligned}$$

(Note that this holds generally and not only at the respective optimal value of e^*.) We further obtain

$$\begin{aligned} \frac{\partial \Pi_S^2}{\partial s^* \partial \lambda_E} &= (1 - e^*) \left[pR^s \Pr[\overline{\theta}|s^*, \overline{h}] - k \right] g(s^*, \overline{h}) \\ &\quad + \frac{e^*}{\gamma \lambda_E^2} \frac{d}{ds^*} \left[\frac{\Pr[\overline{\theta}|s^*, \overline{h}]}{\int_{s^*}^{\overline{s}} \left[\Pr[\overline{\theta}|s, \overline{h}] - \Pr[\overline{\theta}|s^*, \overline{h}] \right] g(s, \overline{h}) ds} \right], \end{aligned}$$

which evaluated at the optimal level of s^*, using (42), becomes

$$\frac{\partial \Pi_S^2}{\partial s^* \partial \lambda_E} = \left[pR^s \Pr[\overline{\theta}|s^*, \overline{h}] - k \right] g(s^*, \overline{h}) \frac{1}{\lambda_E} < 0. \tag{67}$$

Finally, we obtain $\frac{\partial \Pi_S^2}{\partial e^* \partial e^*} = -\frac{2}{\gamma} < 0$. We next use these derivatives to obtain the sign of $ds^*/d\lambda_E$ from total differentiation of the two first-order conditions (42) and (65), using Cramer's rule. With strict concavity, so that the determinant of the Hesse matrix is strictly positive, we thus have that

$$\frac{ds^*}{d\lambda_E} < 0 \iff \frac{\partial \Pi_S^2}{\partial s^* \partial \lambda_E} \frac{\partial \Pi_S^2}{\partial e^* \partial e^*} - \frac{\partial \Pi_S^2}{\partial e^* \partial \lambda_E} \frac{\partial \Pi_S^2}{\partial e^* \partial s^*} > 0, \tag{68}$$

which holds from our previous calculations.

Proof of Proposition 7. Using the notation from the proof of Proposition 3 and substituting from the linear-quadratic specifications, we have for hard-information lending

$$\Pi_H(e^*) = q(e^*)\left[\pi_H - \frac{c'(e^*)}{q'(e^*)}\right] = q(e^*)\left[\pi_H - \frac{e^*}{\gamma\lambda_E}\frac{1}{\Delta_Q}\right]. \tag{69}$$

When interior, this gives rise to the optimally implemented effort

$$e_H^* = \frac{1}{2}\gamma\lambda_E\Delta_Q\pi_H - \frac{1}{2}\frac{Q_M - \lambda_E\Delta_Q}{\lambda_E\Delta} \tag{70}$$

and, after substitution, the profits $\Pi_H^* = \frac{q^2(e_H^*)}{\gamma\lambda_E^2}\frac{1}{(\Delta_Q)^2}$. Likewise, in case of soft-information lending we have

$$\Pi_S(e^*) = q(e^*)\pi_S - \frac{e^*}{\gamma\lambda_E}\frac{1}{\Delta_Q}\left[q(e^*) + \frac{1}{(1-\mu_0)(2\rho-1)}\right], \tag{71}$$

which from the first-order condition gives rise to

$$e_S^* = \frac{1}{2}\gamma\lambda_E\Delta_Q\pi_S - \frac{1}{2}\frac{Q_M - \lambda_E\Delta_Q}{\lambda_E\Delta_Q} - \frac{1}{2\lambda_E\Delta_Q}\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]} \tag{72}$$

Substituting this back, we obtain

$$\Pi_S^* = \frac{1}{\gamma\lambda_E^2}\frac{1}{(\Delta_Q)^2}\left[q^2(e_S^*) + (1-\lambda_E)(Q_M - \lambda_E\Delta_Q)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}] - \Pr[\overline{\theta}|\underline{s},\overline{h}]}\right]. \tag{73}$$

Next, using the envelope theorem, we obtain the respective derivatives

$$\frac{d\Pi_H^*}{dR_E^s} = -\frac{2}{\lambda_E}\frac{1}{\Delta_Q}\frac{dQ_C}{dR_E^s}\Pi_H^* + \frac{2}{\gamma\lambda_E^2}\frac{1}{(\Delta_Q)^2}q(e_H^*)\frac{dQ_C}{dR_E^s}\lambda_E(1-e_H^*), \tag{74}$$

and

$$\begin{aligned}\frac{d\Pi_S^*}{dR_E^s} &= -\frac{2}{\lambda_E}\frac{1}{\Delta_Q}\frac{dQ_C}{dR_E^s}\Pi_S^* \\ &\quad +\frac{1}{\gamma\lambda_E^2}\frac{1}{(\Delta_Q)^2}\frac{dQ_C}{dR_E^s}\left[2q(e_S^*)\frac{dQ_C}{dR_E^s}\lambda_E(1-e_S^*)+\lambda_E\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}\right].\end{aligned}$$

When $\Pi_S^*=\Pi_H^*$, we want to show that $\frac{d\Pi_S^*}{dR_E^s}>\frac{d\Pi_H^*}{dR_E^s}$, which is the case when

$$2q(e_S^*)(1-e_S^*)-2q(e_H^*)(1-e_H^*)+\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}>0. \tag{75}$$

To show this, we can now proceed in perfect analogy to the proof of Proposition 3. For this note first that, for given e^*, $1-e^*=[Q_M-q(e^*)]/(\lambda_E\Delta_Q)$, while when $\Pi_S^*=\Pi_H^*$ we have that

$$q^2(e_H^*)-q^2(e_S^*)=(Q_M-\lambda_E\Delta_Q)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}. \tag{76}$$

With these expressions at hand, condition (75) becomes

$$2Q_M\left[q(e_S^*)-q(e_H^*)\right]+(2Q_M-\lambda_E\Delta_Q)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}>0. \tag{77}$$

Substituting finally for the respective expressions for e_H^* and e_S^*, from (70) and (72) this ultimately transforms to the requirement

$$Q_M(\Delta_Q)^2\gamma\lambda_E^2(\pi_S-\pi_H)+(Q_M-\lambda_E\Delta_Q)\frac{1}{\Pr[\overline{s},\overline{h}]}\frac{\Pr[\overline{\theta}|\underline{s},\overline{h}]}{\Pr[\overline{\theta}|\overline{s},\overline{h}]-\Pr[\overline{\theta}|\underline{s},\overline{h}]}>0, \tag{78}$$

which holds as $\pi_S>\pi_H$. The rest of the argument is as in the proof of Proposition 3.

Appendix B: Loan Rate Competition

As noted in the main text, it remains to confirm the signs of the cross derivatives (47), (48), and (50). For hard-information lending, after noting that $dq/dR^s = dQ_M/dR^s$, we have

$$\frac{d\Pi_H^*}{dR^s} = q(e^*)\Pr[\overline{h}]\Pr[\overline{\theta}|\overline{h}]p + \frac{dQ_M}{dR^s}\left[\pi_H - \frac{e^*}{\gamma\lambda_E}\frac{1}{\Delta_Q}\right]. \tag{79}$$

This yields

$$\begin{aligned}
\frac{d^2\Pi_H^*}{dR^s de^*} &= \lambda_E\Delta_Q\Pr[\overline{h}]\Pr[\overline{\theta}|\overline{h}]p - \frac{dQ_M}{dR^s}\frac{1}{\gamma\lambda_E}\frac{1}{\Delta_Q} > 0, \\
\frac{d^2\Pi_H^*}{dR^s dR_E^s} &= \Pr[\overline{h}]\Pr[\overline{\theta}|\overline{h}]p(1-e^*)\lambda_E\frac{dQ_C}{dR_E^s} - \frac{dQ_M}{dR^s}\frac{e^*}{\gamma\lambda_E}\frac{1}{(\Delta_Q)^2}\frac{dQ_C}{dR_E^s} > 0, \\
\frac{d^2\Pi_H^*}{dR^s d\lambda_E} &= -\left[\Pr[\overline{h}]\Pr[\overline{\theta}|\overline{h}]p(1-e^*)\Delta_Q + \frac{dQ_M}{dR^s}\frac{e^*}{\gamma\lambda_E}\frac{1}{\Delta_Q}\right] < 0.
\end{aligned}$$

Next, using

$$\frac{d\Pi_H^*}{de^*} = \lambda_E\Delta_Q\pi_H - \frac{2}{\gamma}e^* - \frac{1}{\gamma}\frac{Q_M - \lambda_E\Delta_Q}{\lambda_E\Delta_Q}, \tag{80}$$

we have

$$\frac{d^2\Pi_H^*}{de^* dR_E^s} = -\frac{dQ_C}{dR_E^s}\left[\lambda_E\pi_H + \frac{1}{\gamma}Q_M\frac{1}{\lambda_E}\frac{1}{(\Delta_Q)^2}\right] < 0. \tag{81}$$

Finally, to establish the same signs for the case with soft-information lending, observe that

$$\frac{d\Pi_S}{dR^s} = q(e^*)\Pr[\overline{s},\overline{h}]\Pr[\overline{\theta}|\overline{s},\overline{h}]p + \frac{dQ_M}{dR^s}\left[\pi_S - \frac{c'(e^*)}{q'(e^*)}\right] \tag{82}$$

holds in analogy to the case with hard-information lending. The respective cross-derivatives are then easily established.

Notes

[1]See http://www.bls.gov/oco/ocos018.htm

[2]See also Hauswald and Marquez (2003, 2006) for a multi-facetted analysis of the interaction between competition and the acquisition and dissemination of borrower-specific information. In a different vein, Frank (2011) examines the pricing and the quantity of loans when borrowers and lenders have to find each other in a search model.

[3]More generally, our analysis relates to the literature on "delegated expertise", e.g., Lambert (1986), Gromb and Martimort (2007), or Malcomson (2009). Inderst and Ottaviani (2009) examine delegated expertise in the context of consumer protection, while Inderst and Pfeil (2009) examine the process of securitization. Ross (2011) examines the choice between delegating expertise or not in the context of a competitive strategic factor market.

[4]There is evidence that banks that rely on the use of soft information already achieve a very "tight" pre-screening before an application is processed. For instance, Puri, Rocholl and Steffen (2010) document how, prior to the financial crisis, the acceptance rate for household borrowers was over 97 percent in their sample of German savings banks.

[5]The constraint not to condition compensation on loan applications will only bind when the bank uses soft information in its loan-approval decision. In that case, paying for applications could induce loan officers to target pools of potential borrowers who are easier to prospect but who are less credit-worthy (conditional on having positive hard information).

[6]The joint probability is $1-q(e)\sum_{(s,h)\in A}\Pr[s,h] = (1-q(e)) + q(e)\left(1-\sum_{(s,h)\in A}\Pr[s,h]\right)$

[7]To save on notation, $K(e^*;A)$ denotes the costs of compensation at the optimal compensation contract (for a given e^* and A).

[8]We refer to this lending regime as soft-information lending, even though the bank also uses the readily available hard information.

[9]Though we find it more intuitive to express compensation in terms of the conditional probabilities, it can also be readily expressed in terms of the model's primitives:

$$\overline{w} = \frac{c'(e^*)}{q'(e^*)}\frac{1}{p}\frac{\mu_0(\rho_H-\rho_S)+\rho_S(1-\rho_H)}{\mu_0(1-\mu_0)\rho_H(1-\rho_H)(2\rho_S-1)}, \tag{83}$$

$$\underline{w} = \frac{c'(e^*)}{q'(e^*)}\frac{1-\rho_S}{(1-\mu_0)(1-\rho_H)(2\rho_S-1)}. \tag{84}$$

[10]The expression $1+\eta^{-1}$ is a standard measure of market power, as with price competition it measures how much a firm, facing a residual demand curve, can set the price above marginal cost.

[11]To save space, we restrict the exposition to the case when there is indeed a variation in the bank's lending regime as competition changes, i.e., when either lending regime is optimal for some values of λ_E. It is, however, straightforward that soft-information lending is optimal for very low values of λ_E, where both $e_S^* = e_H^* = 0$ (cf. Lemmas 1 and 2).

[12]The argument is identical to the proof of Proposition 2. One only needs to change $\Pr[\overline{\theta}|s,h]$ to $\Pr[\overline{r}|s,h]$ (and set $p=1$). The key is that $\Pr[\overline{r}|\overline{s},\overline{h}] > \Pr[\overline{r}|\underline{s},\overline{h}]$.

[13]We thank an anonymous referee for suggesting this interpretation.

[14]Formally, the derivative is given by

$$\left[\frac{c'(e^*)}{q'(e^*)}\right] \frac{\int_{s^*}^{\overline{s}} \Pr[\overline{\theta}|s,\overline{h}]g(s|\overline{h})ds}{\left[\int_{s^*}^{\overline{s}} \left[\Pr[\overline{\theta}|s,\overline{h}] - \Pr[\overline{\theta}|s^*,\overline{h}]\right] g(s|\overline{h})ds\right]^2} \frac{d\Pr[\overline{\theta}|s^*,\overline{h}]}{ds^*}, \tag{85}$$

where $\frac{d\Pr[\overline{\theta}|s^*,\overline{h}]}{ds^*} > 0$ follows from the strict monotonicity of $\Pr[\overline{\theta}|s,h]$ in s (cf. expression (35)).

[15]See also the discussion in Inderst and Müller (2006) on when corporate loan terms, in particular to small businesses, may indeed be inflexible.