Information Span in Credit Market Competition[*]

Zhiguo He Jing Huang Cecilia Parlatore

August 2025

Abstract

We develop a credit market competition model that distinguishes between information span (breadth) and signal precision (quality), capturing the rise of fintech/non-bank lending where traditionally subjective (soft) information is transformed into objective (hard) data. Borrower quality depends on multidimensional fundamentals, assessed through hard or soft signals. Two banks observe private hard signals, but only the specialized bank receives a soft signal. Expanding the span of hard information enables the non-specialized bank to evaluate characteristics previously only available to the specialist, and reducing its winners curse. By contrast, greater precision of hard signals strengthens the specialized banks informational advantage.

JEL Classification: G21, L13, L52, O33, O36

Keywords: Banking competition, Winner's curse, Specialized lending, Fintech disruption, Information technology, Big Data

---

[*]He: Graduate School of Business, Stanford University, and NBER; email: hezhg@stanford.edu; Huang: Mays Business School, Texas A&M University; email: jing.huang@tamu.edu; Parlatore: Stern School of Business, New York University, NBER, and CEPR; email: cps272@stern.nyu.edu. For helpful comments, we thank Philip Bond, Christa Bouwman, Bruce Carlin, Peter DeMarzo, Itay Goldstein, Veronica Guerrieri, Christopher Hrdlicka, Artashes Karapetyan, Lewis Kornhauser, Dan Luo, Simon Mayer, Michael Ostrovsky, Jonathan Payne, Andy Skrzypacz, Savitar Sundaresan, Anjan Thakor, Laura Veldkamp, Zhe Wang, Basil Williams, Liyan Yang, Jidong Zhou, and participants at Yale Junior Finance Conference, Texas Finance Festival, Lone Star Finance Conference, WAPFIN at Stern, BIS-CEPR-SCG-SFI Financial Intermediation Workshop, FTG meeting, Frankfurt School, Goethe University, Indiana University, Rice University, Northeastern, Yale SOM, UBC Winter Conference, UCL, Women in Macroeconomics Conference, INSEAD Finance Symposium, University of Washington, Annual Paul Woolley Centre Conference at LSE, Oxford Financial Intermediation Theory Conference, Federal Reserve Bank of New York, Duke Fuqua, MIT Sloan, 2024 Fall NBER Corporate Finance Meeting (Stanford), Brown, UTDT, Columbia, Essex-FinteX-WashU-FINEST conference, Cavalcade NA 2025, Mitsui Symposium and EFA 2025. Ningxin Zhang and Jialu Rao provided excellent research assistance. All errors are our own.

As a crucial intermediary sector in modern economies, commercial banks serve as the main conduit between savers and creditworthy borrowers, leveraging a broad spectrum of information. Traditionally, this information involved a mix of hard data—such as financial statements and credit histories—and soft assessments, including borrower reputation, site visits, or managerial judgment. Technological advancements in recent decades have transformed the way information is collected, processed, and used in lending decisions. A notable innovation is the "hardening of soft information" that stems from the "Big Data" revolution. This innovation has transformed qualitative, subjective assessments into quantifiable, objective metrics, expanding the span of hard information—that is, the breadth of characteristics that can now be captured by structured, shareable data. In this paper, we study how this distinct aspect of information technology affects the equilibrium in the credit market.

Agricultural lending illustrates how technology can transform traditional lending practices. Historically, loans to farmers required site visits by specialized loan officers, who relied on experience and local knowledge to assess risks tied to farming techniques, land quality, or infrastructurefeatures often categorized as soft information. Today, satellite imagery and AI-based analytics enable lenders to infer some of these characteristics remotely, using "hard" digitized indicators such as vegetation patterns or soil health scores. Importantly, while this shift has not eliminated the value of soft human expertise, it has extended the *range* of borrower traits that can be assessed via hard signals. This expansion of the information span—not simply an increase in signal precision—is at the core of our analysis.

This remarkable technological advancement has the potential to disrupt the industrial landscape of the banking sector, which motivates us to develop a model that incorporates *information span* in an otherwise standard credit market competition setting. Borrower quality depends on two types of states: hard states, which can be assessed using structured data and modern analytics, and soft states, which require more subjective or specialized knowledge. We consider a "multiplicative" structure so that the borrower repays only if both types of states are favorable. Banks make lending decisions based on private signals about these states: a binary hard signal on the hard state for each lender, and an additional continuous soft signal on the soft state for the specialized lender. We allow hard and soft states to overlap; this overlap and its implications for credit market competition are the main innovation relative to our companion paper Blickle, He, Huang, and Parlatore (2025).

Our framework highlights the difference between breadth (span) and quality (precision) of information. Expanding the span of hard information means that hard signals cover more of the borrowers fundamentals (including dimensions previously considered only soft), while improving its precision increases the accuracy of the signal over a fixed set of traits. Both of these improvements are associated with technological advances that reduce the overall uncertainty faced by lenders. However, we show that changes in the span and the precision of hard information have sharply different impacts on credit market outcomes.

In our model of credit market competition outlined in Section 1, a specialized bank endowed with a binary hard signal and a continuous soft signal competes with a non-specialized bank that has a hard binary signal only. We assume that the hard signal is decisive in that each lender makes an offer only if it receives a positive realization. The soft signal—which differentiates our paper from existing models such as Broecker (1990) and Marquez (2002)—is continuous and guides the fine-tuned interest rate offering of the specialized bank; and when the soft signal realization is sufficiently low, the specialized bank rejects the borrower.

Section 2 characterizes the competitive credit market equilibrium with specialized lending in closed form. The equilibrium is unique and falls into one of two distinct categories depending on whether the non-specialized bank makes zero profits. In the "zero-weak" equilibrium, the Winner's Curse (in competition) faced by the non-specialized "weak" bank is so severe that it randomly withdraws after a positive hard signal, earning zero profits. In the "positive-weak" equilibrium, the Winner's Curse is less severe, and the non-specialized bank always participates upon a positive hard signal and earns positive profits.

The Winners Curse faced by the non-specialized weak bank due to the soft signal being only received by its specialized opponent works through two channels in our setting. The first is standard: it arises from the specialized bank having more precise information about states covered by both hard and soft signals. The second, which is novel to the literature, stems from the specialized bank being the only lender with information about the states covered exclusively by the soft signal–that is, the "only-soft" fundamental states. Shaped by the following three key elements, this latter component drives the distinct effects that span and precision have on equilibrium outcomes:

1. *Probability of facing competition*: the non-specialized bank (who competes only upon a positive hard signal) is concerned about the only-soft fundamental only when the specialized bank also competes (if the opponent also receives a positive hard signal).

2. *Beliefs about soft signal upon competition:* When hard and soft signals are correlated, the event of competition itself conveys information about the soft signal's distribution, leading to a more accurate screening of the soft state.

3. *Inference from winning:* If the non-specialized bank wins the borrower, it infers that the its opponent's soft signal—and thus the only-soft fundamental—is relatively weak.

As our main analysis in Section 3 shows, while both the span and precision of hard information improve lenders' screening ability, they can have opposite effects on the non-specialized bank's beliefs about competition and the quality of the only-soft state, and thus on credit market competitiveness.

An increase in the span of hard information levels the playing field and increases credit market competitiveness. First, a greater span of hard information decreases the probability of competition, as there are more characteristics that need to be positive for a positive hard signal. Second, it leads to an increase in the correlation between hard and soft signals, improving the beliefs about the soft signal received by the specialized bank upon competition. Finally, an increase in span improves the expected quality of the only-soft fundamental, as there are fewer fundamentals that have to be favorable for it to be successful. These effects benefit the non-specialized bank, encouraging participation and increasing competition.

In contrast, a higher precision can increase the Winners Curse faced by the non-specialized bank, strengthening the specialized bank's advantage. An increase in the precision of hard information leads to a higher correlation between hard signals, making them "more public" and hence increasing the probability of competition. The higher correlation also implies that the non-specialized bank's inference about the overlapping states is stronger; hence, for a given soft signal received by the specialized bank, the inference on the only-soft fundamental is weaker. These two effects increase the Winner's Curse and can overcome the improvement in the updating of beliefs about the soft signal upon competition, increasing the informational asymmetries and decreasing credit market competitiveness.

These distinctions arise in the context of credit market competition with specialized lending and multidimensional information. Specialized lending is a practically relevant setting as evidenced by Blickle, He, Huang, and Parlatore (2025).[1] Our structure with multidimensional information is crucial in allowing us to distinguish between span and precision, which, as we show, are distinct aspects of information technology.

Why does the distinction between different types of advancements in information technology matter for our understanding of the world? In principle, recent innovations should enhance hard-information-based screening across the board—specialized incumbent banks can adopt these tools (He, Jiang, Xu, and Yin, 2025), just as effectively as fintech challengers and non-specialized lenders. Yet empirical evidence (see, e.g. Berg, Fuster, and Puri, 2022) suggests that technological change has disproportionately benefited non-specialized, weaker lenders, enabling them to close the gap and intensify competition. Our model, which features asymmetric lenders but symmetric technological improvements, offers an explanation: expanding the information span can robustly generate such outcomes, whereas simply

---

[1] Blickle, He, Huang, and Parlatore (2025) show that banks with asymmetric private information are needed to match the empirical patterns of a lower loan pricing and lower non-default rate among loans granted by specialized lenders.

increasing the precision of existing signals cannot. As illustrated by our motivating example in agricultural lending, Big-Data technologies enlarge the set of measurable borrower characteristics, granting non-specialized lenders access to hardened soft information that was once the exclusive domain of specialized expertise.

This process of "hardening soft information," which expands the span of hard information, has important implications for credit allocation and welfare. We prove that total welfare—measured as the expected surplus from projects that are funded—is always increasing in the span of hard information. Moreover, when hard-signal precision is relatively low, a broader span can also make the specialized bank better off in the positive-weak equilibrium range. This underscores that increases in information span capture industry-wide improvements in information technology that can benefit both specialized and non-specialized lenders.

Finally, we consider two important extensions in Section 4. First, motivated by open banking initiatives, we examine a model with correlated hard signals. We show that an increase in this correlation is qualitatively similar to increasing the hard signal precision and has opposite effects to increasing the hard information span. Second, we introduce an additional signal about the overlapping states as an alternative modeling of hardening of soft information and discuss the robustness of our main takeaway in this alternative setting.

Literature Review

Lending market competition and common-value auctions. In terms of modeling, our framework blends Broecker (1990), who studies credit competition among symmetric bidders with binary signals, and Milgrom and Weber (1982), who consider asymmetric bidders under Blackwell ordering—one with a continuous signal, the other uninformed. In our paper, lenders are privately informed with different hard signals, breaking the Blackwell ordering.[2]

Our companion paper Blickle, He, Huang, and Parlatore (2025) adopts a similar framework to study specialized lending (Blickle, Parlatore, and Saunders, 2023) and explain the empirical pattern that loans from specialized banks have lower rates. The distinction is that in Blickle, He, Huang, and Parlatore (2025), the non-specialized and specialized signals (corresponding to hard and soft signals here) reflect *independent* borrower characteristics that drive the loan quality. This paper, however, allows these underlying states to overlap, enabling us to study how "hardening soft information" affects credit market competition.

In a closely related paper, Karapetyan and Stacescu (2014) argue that sharing borrower's "hard" information (e.g., default history) increases the incumbent bank's incentive to further acquire "soft" information. Their setting always preserves a strict Blackwell ordering, as

---

[2] Within the class of models following Broecker (1990), Hauswald and Marquez (2003) study the competition between an inside bank that can conduct credit screenings and an outside bank without such access; more recent papers include He, Huang, and Zhou (2023) and Goldstein, Huang, and Yang (2022).

shared hard information becomes public. In contrast, we emphasize that span and precision affect competition differently, and conditionally independent hard signals can yield richer empirical and welfare implications.

The nature of soft/hard information in bank lending. The literature on soft vs. hard information (e.g., Stein, 2002; Liberti and Petersen, 2019) emphasizes that hard information is verifiable and thus transferable within organizations, while soft information is often nonverifiable and modeled as cheap talk (e.g., Bertomeu and Marinovic, 2016; Corrao, 2023; Crawford and Sobel, 1982).[3] Since our model does not focus on intra- or inter-bank communication, verifiability is not central to the mechanism we aim to capture. However, our framework complements this traditional view by introducing the concept of information span, which helps explain how technological advances increasingly convert soft information into hard, verifiable data. In our setting, both lenders observe hard signals, but only one accesses the soft signal. Because soft information must be collected and interpreted by specialists, it is not readily shareable; hard information, by contrast, is transferable and can be processed mechanically. As in Karapetyan and Stacescu (2014), once soft information is hardened, it is accessible to non-specialists—leveling the playing field and improving welfare in our model.

Fintech. Our paper connects to the growing literature on fintech disruption (See Berg, Fuster, and Puri, 2022; Vives, 2019). Empirical studies document the use of alternative data in fintech lending, which is consistent with our emphasis on the increasing span of hard information.[4] In particular, Huang, Zhang, Li, Qiu, Sun, and Wang (2020) show that unconventional data from the Alibaba platform, such as business transactions, customer ratings, and consumption patterns improve credit assessment. Ghosh, Vallee, and Zeng (2022) document that the recent development of cashless payments fosters lending, suggesting that the combination of payments and Big Data technology enlarges the span of hard information.

1 Model

In this section, we present our model and highlight the informational structure that is at the core of our analysis.

---

[3] For related empirical studies, see Liberti and Mian (2009), Paravisini and Schoar (2016). He, Jiang, Xu, and Yin (2025) document a significant rise in IT investment among U.S. banks and show that investments in communication technologies enhance banks ability to generate and transmit soft information.

[4] Examples of alternative data include phone device and spelling (Berg, Burg, Gombović, and Puri, 2020), mobile phone logs (Agarwal, Alok, Ghosh, and Gupta, 2020). Along the line of our model with different dimensions of information, Huang (2023) develops a theoretical framework wherein the importance of information concerning underlying qualities varies between collateral-backed bank lending and revenue-based fintech lending such as Square.

1.1 Environment

Consider a credit market competition model with two dates. There are two ex-ante symmetric lenders (banks), indexed by $j \in \{A, B\}$ and one borrower firm; everyone is risk neutral.

Project. At $t = 0$, the firm needs to borrow one dollar to invest in a (fixed-scale) risky project that pays a random cash flow $\tilde{y}$ at $t = 1$. The cash flow realization y depends on the project's quality denoted by $\theta \in \{0, 1\}$. For simplicity, we assume that

$$\tilde{y} = \begin{cases} 1 + \overline{r} & \text{when } \theta = 1 \\ 0 & \text{when } \theta = 0, \end{cases} \tag{1}$$

where $\overline{r} > 0$ is given exogenously, so only the good project pays off. We refer to $\overline{r}$ as the interest rate cap or the return of a good project. The project quality θ is unobservable and the prior probability of a good project is $q \equiv \mathbb{P}(\theta = 1)$. We use "project success," "good project" and/or "good borrower" interchangeably to refer to $\theta = 1$.

Hard and soft states. The project quality $\theta \in \{0, 1\}$ depends on two potentially correlated fundamental states: a "*h*ard" state denoted by θ_h and a "*s*oft" state denoted by θ_s. We assume that both fundamental states are binary so that $\theta_h \in \{0, 1\}$ and $\theta_s \in \{0, 1\}$, with

$$q_h \equiv \mathbb{P}(\theta_h = 1), \text{ and } q_s \equiv \mathbb{P}(\theta_s = 1).$$

Multi-dimensional fundamental states and information span. Following the O-ring theory of economic development by Kremer (1993), we model the hard and soft states in a setting with multidimensional fundamental states. This modeling choice offers a novel way to study the "span" of the information available to banks. More specifically, suppose that the project quality θ depends on N characteristics in the following multiplicative way:

$$\theta = \prod_{n=1}^{N} \theta_n = \overbrace{\prod_{n=1}^{N_h^h} \theta_n \cdot \rlap{$\displaystyle\underbrace{\phantom{\prod_{n=N_h^h+1}^{N_h^h+N_s^h} \theta_n \cdot \prod_{n=N_h^h+N_s^h+1}^{N} \theta_n}}_{\theta_s}$}\prod_{n=N_h^h+1}^{N_h^h+N_s^h} \theta_n}^{\theta_h} \cdot \prod_{n=N_h^h+N_s^h+1}^{N} \theta_n. \tag{2}$$

We assume that $\{\theta_n\}$ follow independent Bernoulli distributions, that is, $\theta_n = 1$ with probability $q_n \in [0, 1]$ for $n = 1, ..., N$, and capture (unobservable) characteristics that are critical to the ultimate success of the project, such as product quality, market and funding conditions, and regulatory environment. As shown in (2), the hard state θ_h covers the first

$N^h \equiv N_h^h + N_s^h$ characteristics, while the soft state covers the last $N - N_h^h$. Importantly, the hard and soft states can overlap in the middle characteristics N_s^h, leading to correlated fundamental states.

Since the order of characteristics plays no role in the analysis, it is without loss of generality to analyze a simplified setting with three independent fundamental states as follows:

$$\theta = \overbrace{\theta_h^h \cdot \underbrace{\theta_s^h}_{}}^{\theta_h}\!\!\!\!\underbrace{\cdot \theta_s^s}_{\theta_s}, \tag{3}$$

with priors denoted by the following:[5]

$$q_h^h \equiv \mathbb{P}\left(\theta_h^h = 1\right), \quad q_s^h \equiv \mathbb{P}\left(\theta_s^h = 1\right), \quad \text{and} \quad q_s^s \equiv \mathbb{P}\left(\theta_s^s = 1\right).$$

Within this framework, θ_h^h in (3) captures those fundamentals only covered by the hard state ("only-hard"), θ_s^s captures the ones that are only covered by the soft state ("only-soft"), and θ_s^h captures the characteristics that are covered by hard and soft states ("overlapping").

Credit market competition. At date $t = 0$, given its private information about the quality of the borrower's project, each bank j makes a take-it-or-leave-it offer to the borrower firm, or makes no offer (exits the lending market). An offer consists of a fixed loan amount of one and an interest rate r. If the borrower firm receives multiple offers, it accepts the offer with the lowest rate.

1.2 Information Technologies

Although project quality is unobservable, lenders have access to information technologies that generate signals about it. We model information technologies as mappings from some fundamental states to signals. We consider two types of technologies modeled as specific mappings from the states θ_h or θ_s to bank-specific signal realizations. To capture specialized lending, we assume that both lenders $j \in \{A, B\}$ have a *hard-information*-based private signal h^j about θ_h, while only the specialized bank A has the *soft-information*-based private signal s about θ_s. Figure 1 provides a visual summary of information technology.

1.2.1 Hard Signals

We assume that both lenders have access to "hard" data (including past financial and operating data, as well as "alternative data" that became available following the "Big Data"

---

[5] Here, $q_h^h = \prod_{n=1}^{N_h^h} q_n$, $q_h^s = \prod_{n=N_h^h+1}^{N_h^h+N_s^h} q_n$, and $q_s^s = \prod_{n=N_h^h+N_s^h+1}^{N} q_n$ given the i.i.d. assumption of $\{\theta_n\}$.

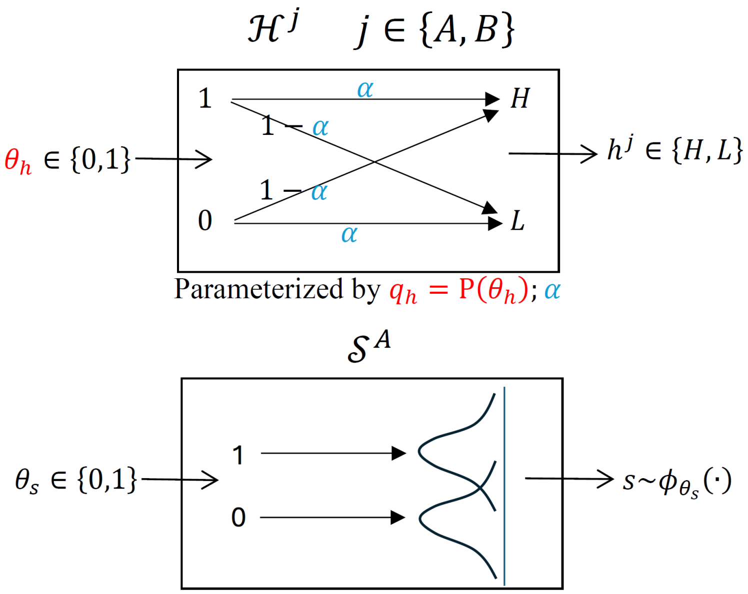


Figure 1: Information Technologies, hard (top panel) and soft (bottom panel)

technology), which they can process to produce a *hard-information*-based private signal h^j about the fundamental state θ_h. We call them "hard" signals.

Hard signal technology For tractability, we assume hard signals are binary, that is, $h^j \in \{H, L\}$, with H (L) being a positive (negative) signal of θ_h. Conditional on the state, hard signals are independent across lenders (Section 4.1 considers correlated hard signals). More specifically, the hard signal technology $\mathcal{H}^j$ takes the binary fundamental hard state $\theta_h \in \{0, 1\}$ as input and generates a binary signal $h^j \in \{H, L\}$ as output. Following most of the literature with exogenous symmetric information technologies (e.g., Broecker, 1990; Marquez, 2002), we assume that

$$\mathbb{P}\left(h^j = H \,|\theta_h = 1\right) = \mathbb{P}\left(h^j = L \,|\theta_h = 0\right) = \alpha \text{ for } j \in \{A, B\} \text{ with } \alpha \in (0.5, 1)\,. \qquad (4)$$

As illustrated in the top panel of Figure 1, α measures the precision of the hard signal and governs the (equal) probabilities of Type I and Type II errors. Given the binary fundamental state θ_h, the hard signal technology $\mathcal{H}^j$ can be summarized by two parameters: the prior $q_h = \Pr(\theta_h)$ of the input θ_h, and the signal's precision α given in (4).

Span of (hard) information The input of the hard information technology, θ_h, is determined by the span of hard information. As the span of hard information increases, the hard state covers more characteristics, corresponding to a larger N_s^h in (2) (or θ_s^h becoming more important in (3)). Hence, an expansion of the coverage of θ_h leads to a smaller q_s^h, as there are more characteristics that have to be one for θ_s^h to be successful. With this in mind, we can define the information span (of hard signals) as

$$\eta \equiv 1 - \Pr(\theta_s^h = 1) = 1 - q_s^h > 0. \tag{5}$$

The span of hard information η controls the input θ_h of the hard information technology $\mathcal{H}^j$. If the soft and hard states are independent, e.g., before soft information gets hardened, this input is $\theta_h = \theta_h^h$ with a prior of $q_h = q_h^h$. As the span of hard information increases, i.e., due to hardening soft information, the input becomes $\theta_h = \theta_h^h \theta_s^h$ with a prior of $q_h = q_h^h q_s^h = (1-\eta) q_h^h$; see (3). From the perspective of the hard signal technology $\mathcal{H}^j$, an increase in the span of hard information only changes the prior of θ_h, i.e., $q_h(\eta) = (1-\eta) q_h^h$, while keeping its precision α constant.[6]

1.2.2 Soft Signal

We further endow Bank A with a signal s to capture the bank being "specialized" in the firm. Similar to Blickle, He, Huang, and Parlatore (2025) we assume that the signal s is continuous. Our preferred interpretation of this additional signal is as a *soft-information*-based private signal, collected after due diligence or face-to-face interactions with the borrower after on-site visits. Besides mathematical convenience, the continuous distribution captures soft information resulting from research tailored to the particular borrower and, therefore, allows for a more granular assessment of the borrower's quality.

The soft signal technology should also be viewed as a mapping $\mathcal{S}^A$ from the soft fundamental state $\theta_s \in \{0, 1\}$ to a variable s that is correlated with θ_s, as in the bottom panel of Figure 1. It is without loss of generality to work directly with the posterior probability of the soft state being favorable given the realization of the soft signal, that is,

$$s \equiv \Pr[\theta_s = 1 | s] \in [0, 1]. \tag{6}$$

Let $\phi(s)ds \equiv \mathbb{P}(s \in (s, s + ds))$ with $\int_0^1 \phi(s)\, ds = 1$ be the density function of s, which satisfies prior consistency $\int_0^1 s\phi(s)\, ds = q_s$. In our numerical examples, we consider $s = \Pr[\theta_s = 1 | \theta_s + \epsilon]$ where $\epsilon \sim \mathcal{N}(0, 1/\tau)$. Here, τ, which is the precision of soft signal (hence analogous to α for the hard signal), captures the signal-to-noise ratio of Bank A's soft information technology.

Denote by $\phi_1(s) \equiv \phi(s | \theta_s = 1)$ the density of s conditional on $\theta_s = 1$. Using the

---

[6] Many existing papers that adopt the binary-fundamental-binary-signal structure, including Marquez (2002), conduct the comparative statics on the prior of the project quality, with the implicit assumption that the signal precision can be kept at a constant.

shorthand notation $s \in ds$ for $s \in (s, s + ds)$, we have

$$\phi_1(s) \equiv \frac{1}{ds}\mathbb{P}(s \in ds|\theta_s = 1) = \frac{\mathbb{P}(\theta_s = 1|s \in ds) \cdot \frac{1}{ds}\mathbb{P}(s \in ds)}{\mathbb{P}(\theta_s = 1)} = \frac{s \cdot \phi(s)}{q_s}. \tag{7}$$

Similarly, we can calculate

$$\phi_0(s) \equiv \phi(s|\, \theta_s = 0) = \frac{(1-s)\phi(s)}{1-q_s}. \tag{8}$$

As the soft signal s is the posterior expectation of θ_s and a higher value of s is "good news," $\phi_1(\cdot)$ and $\phi_0(\cdot)$ satisfy the strict Monotone Likelihood Ratio Property in Milgrom (1981).

1.2.3 Decisive Hard Signals and Parametric Assumptions.

For tractability, we assume that the hard signal is "decisive" for participation: Bank j participates only if it receives $h^j = H$. For the specialized Bank A, the hard signal serves as "pre-screening," in the sense that it rejects the borrower upon receiving an L signal, while upon an H signal it makes a pricing decision based on its soft signal s.[7] We therefore impose the following parameter restrictions to ensure that the hard signal is decisive.

Assumption 1. ***(Decisive Hard Signals)***

1. *Bank A rejects the borrower upon an L hard signal, regardless of any soft signal s:*

$$q_h(1-\alpha)\overline{r} < (1-q_h)\alpha. \tag{9}$$

2. *Bank B is willing to participate if and only if its hard signal $h^B = H$:*

$$q\alpha\overline{r} > (q_h - q)\alpha + (1-q_h)(1-\alpha). \tag{10}$$

Assumption 1 says that the hard signal is sufficiently strong (informative) to serve as pre-screening of loan applications for both lenders. Condition (9) states that it is not profitable for Bank A to lend upon receiving a hard signal L, even when it is the monopolist and quotes the highest possible interest rate $\overline{r}$, and the soft signal reveals that the soft fundamental θ_s

---

[7] Bank A may also rejects the borrower by quoting $r = \infty$ when the soft signal s is sufficiently low. One could interpret the h-signal as "principal", determining whether to lend, and the s-signal as "supplementary" determining loan pricing. Alternatively, the principal signal reflects a credit screening result, while the supplementary signal resembles internal borrower ratings. This ranking highlights the key role of hard information for large banks in assessing new borrowers. As noted by Crawford, Pavanini, and Schivardi (2018), Italian large banks prioritize: (i) central bank data, (ii) Credit Register data, (iii) statistical methods, (iv) bank-specific codified soft information, (v) guarantees, and (vi) branch-level soft information (p. 1677).

is good with certainty. This implies that Bank B, which only has a hard signal, also chooses not to compete upon $h^B = L$. Analogously, Condition (10) states that upon $h^B = H$, Bank B is willing to lend at $\bar{r}$ if it is the monopolist lender. This condition implies that Bank A, with an additional soft signal, is willing to lend at $\bar{r}$ if it is the monopolist lender when $h^A = H$ and the realization of the soft signal is favorable enough.

We also assume that in the population there are more borrowers with favorable hard fundamentals. We use this assumption only in Section 3.2, and it corresponds to the empirically relevant parameter range where a better hard information technology leads to more loan application approvals on average.

Assumption 2. *The prior probability of the hard state being favorable satisfies* $q_h > \frac{1}{2}$.

1.3 Discussion of Assumptions

Multidimensional information, span, and precision. By incorporating multidimensional information, our model distinguishes span from precision—two dimensions of information quality with distinct economic consequences for credit market competition. The information span η, the main innovation in our analysis, captures the breadth of hard information, in contrast to its precision, measured by α for the h-signal and τ for the s-signal. Recent technological advances have improved both. For example, early computing increased the precision of information (e.g. faster processing of bank statements) without expanding its scope. In contrast, Big Data and machine learning have increased the precision of information while, at the same time, broadening what qualifies as hard information by converting subjective or qualitative (soft) data into more objective or quantifiable (hard) metrics (e.g., Amazon's prediction of preferences). For recent evidence of hardening the soft information in the banking industry, see, for example, Hardik (2023).

Hard and soft information. Throughout the paper, we use the hardening of soft information as an example of technological change that can increase the span of hard information. We do this for two reasons: first, to fix ideas and provide a concrete setting in which our model applies; and second, this application is practically relevant in the context of the current "Big Data" environment. However, in the context of Stein (2002), who emphasizes the "verifiability" of hard information relative to soft information, verifiability plays no role in our framework. Instead, our results are broader and apply to any circumstance in which access to information is democratized and characteristics previously accessible only to a monopolist are now "learnable" by all market participants. In particular, we could relabel our analysis in terms of general and specialized information, rather than hard and soft, as in Blickle, He, Huang, and Parlatore (2025).

Binary and symmetric hard signals. The binary structure of the hard signal reflects the coarse way hard information is often used in practice, e.g., credit scores are grouped into five bins despite being calculated on a 300–850 scale. However, our key insight—that information span differs from signal precision—holds under more general settings. We also assume both lenders share the same hard information technology, focusing on how different aspects of technological improvement affect relative market power under symmetric adoption.[8]

Endogenous information structure. Throughout, we take the lenders' asymmetric information technologies as given. Blickle, He, Huang, and Parlatore (2025) endogenize this asymmetric information technology in a symmetric setting with two firms, a and b, where Bank A (B) endogenously becomes specialized by acquiring both hard and soft signals for firm a (b), while non-specialized Bank B (A) only acquires the "hard" signal of the firm a (b). There, we highlight a key difference when acquiring these two types of signals: a one-time investment—for example, installing IT equipment and software—enables lender j to receive two hard signals, one for each firm, whereas soft information must be collected separately for each firm. This is connected to our point regarding the modeling of soft/hard information.

2 Credit Market Equilibrium

We now define and solve for the credit market equilibrium with specialized lending and overlapping information span. Our companion paper (Blickle, He, Huang, and Parlatore, 2025) focuses on the special case of $\eta = 0$, but Proposition 4 in that paper provides a characterization of equilibrium under a general class of information structure that nests our model.[9] Our exposition below thus emphasizes the key equilibrium properties, highlighting how they differ from those in the $\eta = 0$ benchmark.

2.1 Credit Market Equilibrium Definition

Define the space of interest rate offers as $\mathcal{R} \equiv [0, \overline{r}] \cup \{\infty\}$; recall $\overline{r}$ is the exogenous return for the good project in (1) and ∞ captures not making an offer.[10]

For Bank A, we denote its pure strategy by $r^A(s) : [0,1] \to \mathcal{R}$,[11] which induces a

---

[8] In the companion paper Blickle, He, Huang, and Parlatore (2025), we consider a general (binary) information technology that is potentially asymmetric between lenders.

[9] Blickle, He, Huang, and Parlatore (2025) characterize the credit market equilibrium under two key conditions: i) decisive binary signals, and ii) the two binary signals and the continuous one are independent *conditional* on project success. Our setting with arbitrary information spans satisfies both of these conditions.

[10] Alternatively, $\overline{r}$ can also be interpreted as exogenous maximum (usury) interest rate. For instance, in Illinois the usury rate for most consumer loans is capped at 36% APR.

[11] We formally prove that in equilibrium Bank A uses pure strategies in Proposition 1.

distribution of its interest rate offers, denoted by $F^A(r) \equiv \Pr\left(r^A \leq r\right)$ according to the underlying distribution of the soft signal. We refer to the endogenous support of interest rates when making an offer as the "support" of the interest rate distribution, even though loan rejection ($r = \infty$) could also occur along the equilibrium path.

Conditional on a positive hard signal, Bank B randomizes its interest rate offers drawing from an endogenous distribution $F^B(r) \equiv \Pr\left(r^B \leq r\right)$. Since the domain of offers includes $r = \infty$ (i.e., rejection), it is possible that $F^B(\overline{r}) = \mathbb{P}\left(r^B < \infty | h^B = H\right) < 1$.

The borrower picks the lower rate offered, choosing each rate with equal probability if the two rates offered are equal. This implies that, conditional on $h^A = h^B = H$, if Bank B quotes $r^B < \infty$ its winning probability is $1 - F^A\left(r^B\right)$, which equals the probability that Bank A offers a rate that is higher than r^B. Note that this includes the event that Bank A rejects the borrower ($r^A(s) = \infty$), presumably because of an unfavorable soft signal. If $r^A = r^B = \infty$, the borrower receives no loan.

Definition 1. (**Credit market equilibrium**) A competitive equilibrium in the credit market (with decisive hard signals) consists of the following strategies:

1. A lender j rejects the borrower or $r^j = \infty$ upon $h^j = L$ for $j \in \{A, B\}$; upon $h^j = H$,
    - i) Bank A offers $r^A(s) : [0,1] \to \mathcal{R} \equiv [0, \overline{r}] \cup \{\infty\}$ to maximize its expected profits given $h^A = H$ and s, which induces a distribution function $F^A(r) : \mathcal{R} \to [0,1]$;
    - ii) Bank B offers $r^B \in \mathcal{R}$ to maximize its expected profits given $g^B = H$, which induces a distribution function $F^B(r) : \mathcal{R} \to [0,1]$;
2. The borrower chooses the lowest offer $\min\{r^A, r^B\}$.

As is standard (e.g., Broecker, 1990), there exists an endogenous lower bound on interest rates $\underline{r} > 0$, so that the two distributions $F^j(\cdot)$, $j \in \{A, B\}$ share a common support $[\underline{r}, \overline{r}] \cup \{\infty\}$. The following lemma shows that the equilibrium strategies in our setting are well-behaved.

Lemma 1. *(**Well-behaved Equilibrium Strategies**) In any credit market equilibrium:*

a. The two lenders' interest rate distributions $F^j(\cdot)$, $j \in \{A, B\}$ are smooth over $[\underline{r}, \overline{r})$, that is, no gaps and atomless, so that they admit well-defined density functions;

b. At most only one lender can have a mass point at $\overline{r}$.

Proof. See Online Appendix B.1. □

2.2 Bank Profits and Optimal Strategies

Before computing the banks' profits and optimal strategies, we define the relevant probabilities and posterior beliefs, which are key elements in the characterization of the equilibrium.

2.2.1 Joint Distributions of Signals and Posterior

Denote by the ordered subscript $\{h^A h^B\} \in \{HH, HL, LH, LL\}$ the events of the corresponding hard signal realizations, where HL stands for Bank A's hard signal being H and Bank B's hard signal being L. Denote by $\overline{p}_{h^A h^B}$ the joint probability of any collection of hard signal realizations; here, the "bar" indicates taking the average over all possible soft signal realizations. For instance,

$$\overline{p}_{HH} \equiv \mathbb{P}\left(h^A = H, h^B = H\right) = q_h \alpha^2 + (1 - q_h)(1 - \alpha)^2 . \tag{11}$$

Denote by $\overline{\mu}_{h^A h^B}$ the posterior probability of project success conditional on $h^A h^B$; for instance

$$\overline{\mu}_{HH} \equiv \frac{\mathbb{P}\left(h^A = H, h^B = H, \theta = 1\right)}{\mathbb{P}\left(h^A = H, h^B = H\right)} = \frac{q_h \alpha^2}{q_h \alpha^2 + (1 - q_h)(1 - \alpha)^2} q_s^s. \tag{12}$$

Upon competition, lenders also need to assess the joint probabilities of the hard and soft signals. Denote by $p_{h^A h^B}(s)\, ds \equiv \mathbb{P}\left(h^A, h^B, s \in ds\right)$ the joint probability of the two hard signals being $h^A h^B$ and $s \in ds$, that is, the soft signal s falls in the interval $(s, s + ds)$. Similarly, $\mu_{h^A h^B}(s)$ denotes the posterior probability of project success $\theta = 1$, conditional on the realizations of all signals:

$$\mu_{h^A h^B}(s) = \mathbb{P}\left(\theta = 1 | \, h^A, h^B, s\right) = \frac{\mathbb{P}\left(\theta = 1, h^A, h^B, s \in ds\right)}{\mathbb{P}\left(h^A, h^B, s \in ds\right)}. \tag{13}$$

Under the multiplicative structure in (3), project success $\theta = 1$ implies that $\theta_h = \theta_s = 1$, which allows us to derive the joint probability of $\mathbb{P}\left(\theta = 1, h^A, h^B, s \in ds\right)$ as

$$p_{h^A h^B}(s)\, \mu_{h^A h^B}(s) = \mathbb{P}(\theta = 1) \cdot \mathbb{P}\left(h^A \, | \theta_h = 1\right) \cdot \mathbb{P}\left(h^B \, | \theta_h = 1\right) \cdot \phi\left(s | \, \theta_s = 1\right). \tag{14}$$

2.2.2 Bank A's Strategy

Suppose that Bank A observes a positive hard signal $h^A = H$ and a soft signal s. If it exits the lending market by quoting $r = \infty$, its expected profits are $\pi^A(r = \infty, s) = 0$. If it offers a rate $r \in [\underline{r}, \overline{r}]$, Bank A's expected profits are

$$\pi^A(r,s) \equiv p_{HH}(s)\left[1 - F^B(r)\right]\left[\mu_{HH}(s)(1+r) - 1\right] + p_{HL}(s)\left[\mu_{HL}(s)(1+r) - 1\right]. \tag{15}$$

The first term captures the case where both banks receive positive signals, and Bank A wins with probability $1 - F^B(r)$; the second term accounts for the case where Bank B receives a negative hard signal and exits. Since Bank B randomizes its strategy upon $h^B = H$, from Bank A's perspective, winning the price competition is not informative about the borrower's quality (so the belief about borrower quality $\mu_{HH}(s)$ in the first term in (15) is unaffected by $1 - F^B(r)$). However, whether B participates or not informs A's expected quality of the borrower, as captured by $\mu_{HH}(s)$ in the first term and $\mu_{HL}(s)$ in the second term in (15).

Given the profit function defined above, Bank A's optimal interest rate offer is $r^A(s) \equiv \arg\max_{r \in \mathcal{R}} \pi^A(r,s)$, which is decreasing in s (see Proposition 1), hits the interest rate cap $\overline{r}$ when the soft signal worsens (at some threshold $\hat{s}$), and in general will jump to ∞ for sufficiently low s (at another threshold x). In the interior range where $r^A(s) \in [\underline{r}, \overline{r})$, that is for $s \in (\hat{s}, 1]$, we define $s^A(r) \equiv r^{A(-1)}(r)$ as the realization of the soft signal s that induces bank A to offer a rate r. This mapping plays a crucial role in Bank B's beliefs about the soft fundamental state.

2.2.3 Bank B's Strategy

While Bank A updates its beliefs about borrower quality only based on Bank B's participation, since, as explained after (15), the rate offered by Bank A conveys information about the soft signal realization, subjecting Bank B to an additional Winner's Curse. More specifically, besides the possibility of the specialized lender A's unfavorable hard signal, the non-specialized lender B who wins the price competition also infers that $r^A(s) > r^B$, which implies $s < s^A\left(r^B\right)$ (recall $r^A(s)$ is decreasing). Taking these unfavorable inferences into account, Bank B's lending profits when quoting r are

$$\pi^B(r) \equiv \int_0^{s^A(r)} p_{HH}(t)\left[\mu_{HH}(t)(r+1) - 1\right] dt + \overline{p}_{LH}\left[\overline{\mu}_{LH}(r+1) - 1\right]. \tag{16}$$

The first term in (16) captures Bank A seeing $h^A = H$ and competing, while the second term considers $h^A = L$ and Bank A not participating. Bank B infers the project's quality based on the event of "winning the borrower"—which occurs when Bank A receives an unfavorable soft signal realization $s < s^A(r)$. Importantly, this inference, which is informative about θ_s and θ_h when the spans of hard and soft information overlap, is at the heart of our analysis of how different information technologies affect the credit market equilibrium.

To see this more clearly, using (14) one can write Bank B's profits in (16) as

$$\pi^B(r) = \int_0^{s^A(r)} q\alpha^2\phi_1(t)\,dt \cdot (1+r) - \int_0^{s^A(r)} p_{HH}(t)\,dt + \overline{p}_{LH}\left[\overline{\mu}_{LH}(\overline{r}+1)-1\right]. \tag{17}$$

The first term reflects the expected revenue of lending at r, given by the updated probability that the project is good, that is, $\int_0^{s^A(r)} q\alpha^2\phi_1(t)\,dt$, multiplied by loan repayment $1+r$. Importantly, as we discuss in the next section, the span η only affects the expected revenue of the loan through $s^A(r)$, whereas α also affects revenue directly through screening ($q\alpha^2\phi_1(t)$).

The second term is the expected cost of lending to borrowers with low soft signal realizations ($s < s^A(r)$). This cost—derived largely from the residual uncertainty Bank B has about θ_s^s—represents the Winner's Curse in competition. Bank B is concerned that Bank A's expected quality of the only-soft state $z_s^s(s) \equiv \mathbb{E}\left[\theta_s^s | HHs\right]$ may be too low, reflecting a low soft signal realization and a weak borrower (one can show that $z_s^s(s)$ is strictly increasing in the soft signal realization s). Thus, the Winner's Curse upon competition depends on the left tail of Bank B's perceived distribution of z_s^s given by

$$\Pr\left(z_s^s(t) < \hat{z}\right) = \Pr\left(t < z_s^{s(-1)}(\hat{z})\right) = \int_0^{z_s^{s(-1)}(\hat{z})} p_{HH}(t)\,dt, \tag{18}$$

where $z_s^{s(-1)}(\hat{z})$ is the realization of the soft signal that induces a belief $\hat{z}$ about θ_s^s for Bank A. Note that (18) has the same structure as the second term in (17). In Section 3.2 we examine how information technology affects this left tail and Bank B's learning from winning.

Hence, after observing $h^B = H$, Bank B chooses its strategy $F^B(\cdot)$ to maximize its expected payoff

$$\max_{F^B(\cdot)} \int_{\mathcal{R}} \pi^B(r)\,dF^B(r). \tag{19}$$

Since profit-maximizing Bank B plays mixed strategies, $\pi^B = \pi^B(r)$ for all $r \in [\underline{r}, \overline{r}]$.

2.3 Credit Market Equilibrium Characterization

Following Blickle, He, Huang, and Parlatore (2025), we first take Bank B's equilibrium profits π^B as given to derive lenders' strategies. Similar to Milgrom and Weber (1982), it is relatively easy to solve for Bank A's equilibrium strategy by invoking Bank B's indifference condition, i.e., Bank B makes the same profit across all rates on the support $[\underline{r}, \overline{r}]$. Plugging in $r = r^A(s)$ in Bank B's profit in (16), and using $\pi^B(r) = \pi^B, \forall r \in [\underline{r}, \overline{r}]$, we have

$$\pi^B = \underbrace{\left[\int_0^s p_{HH}(t)\mu_{HH}(t) + \overline{p}_{LH}\overline{\mu}_{LH}\right]}_{\text{borrowers who repay}}\left(1 + r^A(s)\right) - \underbrace{\left(\int_0^s p_{HH}(t)dt + \overline{p}_{LH}\right)}_{\text{lending cost}}. \tag{20}$$

Solving for $r^A(s)$ yields (26) in Proposition 1 below, which further takes into account the necessary truncation on the interest rate cap $\overline{r}$.

Although the derivation of Bank B's equilibrium strategy is more involved, conceptually it is quite simple: Bank B's equilibrium strategy needs to support $r^A(\cdot)$ in (26) as Bank A's optimal strategy. A detailed derivation is provided in the companion paper Blickle, He, Huang, and Parlatore (2025); here we summarize the key steps and show that the methodology applies to overlapped hard and soft states.

Let $Q^A(r; s)$ and $Q^B(r)$ denote the total "effective" borrower (who can repay) of lenders A and B, respectively, when they offer an interest rate r. Note, $Q^A(r; s)$ depends on s because Bank A also knows the soft signal s (while Bank B does not):

$$Q^A(r; s) = p_{HH}(s)\mu_{HH}(s)\left[1 - F^B(r)\right] + p_{HL}(s)\mu_{HL}(s), \tag{21}$$

$$Q^B(r) = \int_0^{s^A(r)} p_{HH}(t)\mu_{HH}(t)dt + \overline{p}_{LH}\overline{\mu}_{LH}. \tag{22}$$

Bank A's first-order condition (FOC) balances the higher probability of winning ($Q^{A\prime}(r; s)dr$) when cutting its rate against a lower payoff from served borrowers ($Q^A(r; s)dr$):

$$\underbrace{Q^{A\prime}(r; s) \cdot \left(1 + r - \frac{1}{\mu_{HH}(s)}\right)}_{\text{MB on marginal borrower type}} = \underbrace{-Q^A(r; s)}_{\text{MC on existing borrower types}}. \tag{23}$$

The term inside the parentheses on the left-hand side in (23) concerns the marginal borrower with quality $\mu_{HH}(s)$. Due to imperfect screening, A incurs a total lending cost of $\frac{1}{\mu_{HH}(s)}$ to serve each good borrower who repays $1 + r$. Similarly, to maximize (16), B's FOC balances the change in its borrowers ($Q^{B\prime}(r)$) against the gain from existing borrowers ($-Q^B(r)$):

$$\underbrace{Q^{B\prime}(r) \cdot \left(1 + r - \frac{1}{\mu_{HH}(s^A(r))}\right)}_{\text{MB on marginal borrower type}} = \underbrace{-Q^B(r)}_{\text{MC on existing borrower types}}. \tag{24}$$

Here, Bank B who quotes r infers the quality of the marginal borrower $\mu_{HH}(s^A(r))$ based on Bank A's equilibrium strategy; see Appendix B.2 for detailed derivations of (23) and (24).

Importantly, both lenders are competing for the same marginal borrower (type) at any interest rate $r \in [\underline{r}, \overline{r})$, that is, $1 + r - \frac{1}{\mu_{HH}(s^A(r))}$. In fact, evaluating (23) at the equilibrium borrower type $s = s^A(r)$ and combining it with (24), we arrive at the following:

$$\frac{Q^{A\prime}\left(r; s^A(r)\right)}{Q^A\left(r; s^A(r)\right)} = \frac{Q^{B\prime}(r)}{Q^B(r)} \Leftrightarrow \frac{d}{dr}\left[\frac{Q^A(r; s)}{Q^B(r)}\right]\Bigg|_{s=s^A(r)} = 0. \tag{25}$$

As lenders balance the same marginal borrower's payoff with the payoff gain from existing customers, in equilibrium, their existing effective customers should change proportionally, as shown in (25). Using this, one can solve for Bank B's equilibrium strategy in Proposition 1.

Lastly, Bank B's equilibrium profit π^B depends on which lender first breaks even when quoting $\overline{r}$ as s decreases: either Bank B breaks even with $\pi^B = 0$, or Bank A breaks even upon $s = \hat{s}$, which renders $\pi^B > 0$. The next proposition characterizes the credit market equilibrium in closed form.

Proposition 1. ***(Credit Market Equilibrium)*** *In the credit market equilibrium, Bank A follows a pure strategy as in Definition 1. In this unique equilibrium, lenders reject borrowers upon a negative hard signal realization* $h^j = L$ *for* $j \in \{A, B\}$*. Otherwise (i.e., when* $h^j = H$*), their strategies are characterized as follows:*

1. *Bank A with soft signal s offers*

$$r^A(s) = \begin{cases} \min\left\{\frac{\pi^B + \int_0^s p_{HH}(t)dt + \overline{p}_{LH}}{\int_0^s p_{HH}(t)\cdot\mu_{HH}(t)dt + \overline{p}_{LH}\overline{\mu}_{LH}} - 1, \overline{r}\right\}, & \text{for} \quad s \in [x, 1] \\ \infty, & \text{for} \quad s \in [0, x). \end{cases} \tag{26}$$

   The equation pins down $\underline{r} = r^A(1)$*. For* $s \in (\hat{s}, 1]$ *where* $\hat{s} = \sup s^A(\overline{r})$*,* $r^A(\cdot)$ *is strictly decreasing with its inverse function* $s^A(\cdot) = r^{A(-1)}(\cdot)$*.*

2. *Bank B makes an offer with cumulative probability given by (*$\mathbf{1}_{\{X\}} = 1$ *if X holds)*

$$F^B(r) = \begin{cases} 1 - \frac{\int_0^{s^A(r)} t\phi(t)dt}{q_s}, & \text{for} \quad r \in [\underline{r}, \overline{r}), \\ 1 - \mathbf{1}_{\{\pi^B = 0\}} \cdot \frac{\int_0^{\hat{s}} t\phi(t)dt}{q_s}, & \text{for} \quad r = \overline{r}. \end{cases} \tag{27}$$

   When $\pi^B = 0$*,* $F^B(\overline{r}) = F^B(\overline{r}^-) \leq 1$ *is the probability that Bank B makes the offer (and with probability* $\frac{1}{q_s}\int_0^{\hat{s}} t\phi(t)\,dt$ *it withdraws by quoting* $r^B = \infty$*); when* $\pi^B > 0$*,* $F^B(\overline{r}) = 1$ *and there is a point mass of* $\frac{1}{q_s}\int_0^{\hat{s}} t\phi(t)\,dt$ *at* $\overline{r}$*.*

3. *The equilibrium Bank B's profit is given by*

$$\pi^B = \max\left(\hat{\pi}^B\left(\overline{r}; s^A(\overline{r}) = s_A^{be}\right), 0\right), \tag{28}$$

   where s_A^{be} *is the unique solution to* $\hat{\pi}^A\left(\overline{r}|s_A^{be}; F^B(\overline{r}) = \int_{s_A^{be}}^1 \frac{s\phi(s)dt}{q_s}ds\right) = 0$ *with auxiliary functions* $\hat{\pi}^B(\cdot;\cdot)$ *and* $\hat{\pi}^A(\cdot|\cdot;\cdot)$ *defined in Online Appendix B.2.*

Proof. See Appendix A.1 for proof outline, and Online Appendix B.2 for proof. □

In Proposition 1, point 1) shows that Bank A offers a higher interest rate as the soft signal deteriorates. Threshold $\hat{s}$ is the highest soft signal where Bank A offers the interest rate cap $\overline{r}$, while threshold $x \leq \hat{s}$ is where Bank A breaks even when offering $\overline{r}$—$\pi^A(\overline{r}, x) = 0$. If $\hat{s} > x$, Bank A holds some monopolistic power as it makes positive profits when offering the monopolistic rate $\overline{r}$. If $\hat{s} = x$, Bank A breaks even when offering $\overline{r}$.

Bank B's equilibrium strategy is characterized in point 2). If $\pi^B = 0$, Bank B randomly chooses to exit the credit market upon receiving a positive hard signal, reflected by $F^B(\overline{r}) < 1$. If $\pi^B > 0$, Bank B always participates upon receiving a positive hard signal ($F^B(\overline{r}) = 1$) and places mass at the interest rate cap $\overline{r}$. In the first case, the Winner's Curse is strong enough to deter Bank B's participation, granting Bank A monopolistic power. In the second, the Winner's Curse is weaker, and Bank B can make a profit by offering $\overline{r}$ and winning the borrower only when Bank A receives a soft signal $s < x$.

The equilibrium strategies in Proposition 1 in points 1) and 2) depend on the equilibrium profits π^B, and point 3) shows that π^B is pinned down by model primitives (subject to solving for one endogenous constant s_A^{be}). In the *zero-weak* equilibrium $\pi^B = 0$ and only Bank A puts mass on $\overline{r}$. In the *positive-weak* equilibrium $\pi^B > 0$, and only Bank B does so. These outcomes are consistent with point b) in Lemma 1—otherwise, lenders would undercut each other at the interest rate cap $\overline{r}$.

2.4 Credit Market Equilibirum under Hardening Soft Information

To fix ideas, we illustrate numerically how the information span η affects the credit market competition equilibrium in Figure 2. We interpret this increase in information span as the outcome of hardening soft information, which makes information—once held only specialists—accessible to non-specialists too. For ease of exposition, we assume that Bank A's soft signal s is obtained from observing a noisy version of θ_s, i.e., $\theta_s + \epsilon$, so that $s = \mathbb{E}[\theta_s | \theta_s + \epsilon]$. Here, $\epsilon \sim \mathcal{N}(0, 1/\tau)$ indicates white noise, with the precision parameter τ capturing the signal-to-noise ratio of Bank A's soft information technology.

The top two panels in Figure 2 plot both lenders' pricing strategies conditional on making an offer, with Panel A plotting $r^A(s)$ as a function of s for Bank A and Panel B the density $F^{B\prime}(r)$ as a function of r for Bank B. We plot the equilibrium pricing strategies for two levels of information span η: the baseline $\eta_0 = 0$, and a higher $\eta_+ = 0.05$. A positive (zero) weak equilibrium arises when η is relatively high (low), hence the subscript "+" for the higher η.

As hardening soft information (a higher η) reduces the informational asymmetries, Bank B becomes more aggressive as its distribution of offered rates shifts downward (panel B), resulting in a smaller equilibrium lower bound $\underline{r}_+ < \underline{r}_0$. In response to the more aggressive

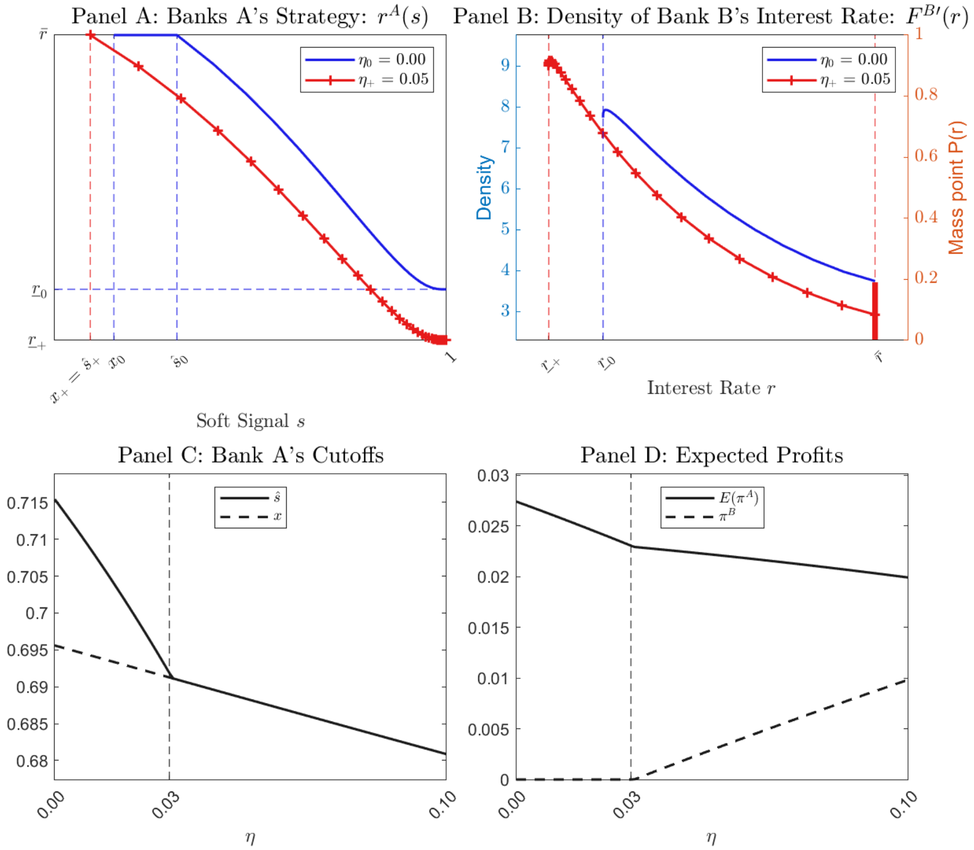


Figure 2: **Equilibrium strategies and profits for information span η.** Panel A depicts $r^A(s)$ as a function of s and Panel B plots $F^{B\prime}(r)$ as a function of r; strategies for $\eta_+ = 0.05$ are depicted in red with markers while strategies with $\eta_0 = 0$ are depicted in blue. Panel C depicts Bank A's thresholds $\hat{s} = \sup s^A(\bar{r})$ and $x = \sup s^A(\infty)$, and Panel D depicts the expected profits for two lenders, both as a function of η. Parameters: $\bar{r} = 0.36$, $q = 0.72$, $q_s = 0.9$, $\alpha = 0.7$, and $\tau = 1$.

bidding by Bank B,we see that the entire curve $r^A(s)$ shifts downward.

Panel C plots the two soft signal cut-offs for the specialized Bank A, i.e., $\hat{s} \equiv \sup s^A(\bar{r})$ at which it starts quoting $\bar{r}$ and $x \equiv \sup s^A(\infty)$ at which it starts rejecting the borrower. For a sufficiently large η, $\hat{s}$ and x coincide reflecting a zero probability mass on the interest rate cap $\bar{r}$. Finally, Panel D plots the expected profits—$\mathbb{E}(\pi^A)$ and π^B—for both lenders; when η increases, the non-specialized lender becomes relatively stronger, leading to a strictly positive π^B as shown in Panel D.

These panels show how hardening soft information "levels the playing field." Intuitively, for a small span η, the Winner's Curse is too strong as to deter full participation by Bank B and the equilibrium is zero-weak, where the specialized Bank A places a point mass on $\bar{r}$ (when $s \in (x, \hat{s})$, as shown in Panel C). In contrast, as soft information gets hardened and η is large enough, the Winner's Curse faced by the non-specialized Bank B due to the opponent's soft signals becomes relatively minor. This intensifies competition, and leads to a positive-weak equilibrium, where the non-specialized Bank B becomes profitable—so that it enjoys some "local monopoly power" by placing a point mass on $\bar{r}$. We explore these mechanisms formally in the next section.

3 Span vs. Precision

A key advantage of our model is that it allows us to distinguish between aspects of information technology. Our model isolates the span and precision of information, allowing us to examine their distinct effects on the credit market equilibrium.

3.1 Screening Technology

First, we show that both an increase in the span of hard information and in its precision are indeed technological improvements in the sense that they increase the hard signals' screening quality for the project quality θ. To see this, let

$$z\left(H\right) \equiv \mathbb{E}\left[\theta = 1 \middle| h^B = H\right] = \frac{\mathbb{P}\left(\theta = 1, h^B = H\right)}{\mathbb{P}\left(h^B = H\right)}. \tag{29}$$

This expression represents the expected project quality for Bank B upon receiving a positive hard signal.[12] As Lemma 2 below shows, $z\left(H\right)$ is increasing in η and α. On one hand, a larger span η implies that a positive hard signal indicates more fundamental states to be favorable, and hence increases the expected project quality. On the other hand, a higher precision makes the realized high hard signal more informative about the underlying fundamental, which also leads to a higher expected project quality. This can be seen in Figure 3.

Lemma 2. ***(Improved Screening)*** *The posterior project quality upon receiving a high hard signal, $z\left(H\right)$, is increasing in the span of hard information η and in its precision α.*

Proof. See Appendix A.2. ☐

3.2 Learning upon Winning

While increases in the span and precision of hard information similarly improve overall screening efficiency with respect to the project quality θ, they can have opposite effects on Bank B's residual uncertainty about the only-soft state θ_s^s. Since Bank B's beliefs about θ_s^s after receiving a positive hard signal determine the severity of the Winners Curse it faces,

---

[12] Given the symmetry in the hard signals for the lenders, $z\left(H\right)$ also measures the posterior quality for Bank A after only observing a high hard signal.

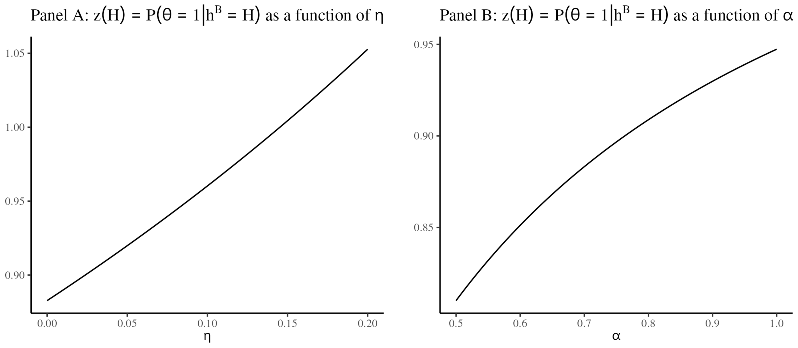


Figure 3: $z(H)$ **and information technology.** Panel A plots $z(H)$ as a function of η and Panel B plots $z(H)$ as a function of α. Parameters: $\alpha = 0.85, \eta = 0.05, q_h^h = 0.9$, and $q_s = 0.9$.

this residual uncertainty is key to understanding how changes in information technology shape credit market competition.

We first compute the expected quality of the only-soft state when both lenders get a high hard signal and the specialized bank gets a soft signal s:

$$z_s^s(s) \equiv \mathbb{E}\left[\theta_s^s = 1 | HHs\right] = \frac{\mathbb{P}\left(\theta_s^s = 1, h^A = h^B = H, s\right)}{\mathbb{P}\left(HHs\right)}. \tag{30}$$

Appendix A.3.1 gives the expression for (30), which depends on both the span η and the precision α of hard information.

In (30), $z_s^s(s)$ captures the expected quality of θ_s^s for Bank A when it observes signal s upon competition. Bank B, however, does not observe the soft signal realization s. Hence, Bank B is concerned about winning the competition for the borrower, only because the better-informed Bank A has received an unfavorable soft signal (Winner's Curse). More specifically, similar to the reasoning provided in Section 2.2.3 after (18), Bank B (conditional on $h^B = H$ and hence compete) cares about the left tail of the distribution of z_s^s, which, fixing any cutoff $\hat{z}$, is given by

$$\begin{aligned}\mathbb{P}\left(z_s^s(s) < \hat{z} | h^B = H\right) &= \mathbb{P}\left(s < z_s^{s(-1)}(\hat{z}) | h^B = H\right) = \int_0^{z_s^{s(-1)}(\hat{z})} \frac{p_{HH}(s)}{\mathbb{P}(h_B = H)} ds \\ &= \underbrace{\mathbb{P}\left(HH | \, h^B = H\right)}_{\text{prob. of facing competition}} \int_0^{\underbrace{z_s^{s(-1)}(\hat{z})}_{\text{inferring } \theta_s^s}} \underbrace{\phi\left(s \,| HH\right)}_{s \text{ distribution in competition}} ds.\end{aligned} \tag{31}$$

There are three channels through which information technology can affect the expression in (31). The first channel is by changing the probability of Bank B facing competition upon receiving a high hard signal. The second channel is through Bank B's inference about the only-soft fundamental θ_s^s upon winning. The third channel is by affecting the beliefs about the distribution of the soft signal upon competition. We analyze each of these effects below.

3.2.1 Probability of Facing Competition

The less informed Bank B cares about the realization of the soft signal—and the associated Winner's Curse—only when it expects to face competition for the borrower. That is, when Bank A receives a positive hard signal, given that Bank B receives one too. The first term in (31) captures the probability that Bank B assigns to this event upon observing $h^B = H$. Interestingly, the span and precision of hard information have opposite effects on this term, as Lemma 3 below show.

Lemma 3. ***(Beliefs about Competition)*** *The span and precision of hard information have opposite effects on* $\mathbb{P}\left(HH|\, h^B = H\right)$*. More specifically,*

$$\frac{d\mathbb{P}\left(HH|\, h^B = H\right)}{d\eta} < 0 \quad \textit{and} \quad \frac{d\mathbb{P}\left(HH|\, h^B = H\right)}{d\alpha} > 0.$$

Proof. See Appendix A.3.2. ☐

Intuitively, as the information span η increases, the hard signal reflects a broader range of fundamentals. Under a multiplicative structure, this makes it less likely for either bank to receive a positive hard signal since it requires more fundamental states to be favorable. As a result, the two hard signals become less correlated, reducing the probability that Bank B faces competition. Because $\mathbb{P}\left(HH|\, h^B = H\right)$ scales the left tail in (31), this reduction in competition mitigates the Winner's Curse on the soft signal faced by Bank B.

In contrast, as the precision of the hard signal increases, the two hard signals become more correlated, increasing the probability that Bank A also receives a positive signal given that Bank B does. In the extreme case where $\alpha = 1$, the hard signals are perfectly correlated and effectively public. Thus, a higher precision increases Bank B's perceived likelihood of facing competition upon receiving a positive signal, intensifying the Winner's Curse. Panel I in Figure 4 illustrates this comparison by plotting $\mathbb{P}\left(HH|\, h^B = H\right)$ against both η and α.

3.2.2 Inference from Winning

The second effect relates to the residual uncertainty about θ_s^s, captured by the integration limit $z_s^{s(-1)}\left(\hat{z};\eta,\alpha\right)$ in (31). This threshold represents the value of the soft signal received by Bank A that would induce a posterior belief $z_s^s = \hat{z}$ about θ_s^s. As shown in the lemma below, η and α have opposite effects on this threshold.

Lemma 4. ***(Inference about*** θ_s^s***)*** *The span and precision of hard information have opposite effects on* $z_s^{s(-1)}(\hat{z};\eta,\alpha)$*. More specifically,*

$$\frac{dz_s^{s(-1)}(\hat{z};\eta,\alpha)}{d\eta} < 0, \quad \textit{while} \quad \frac{dz_s^{s(-1)}(\hat{z};\eta,\alpha)}{d\alpha} \geq 0 \ \textit{if} \ z_s^{s(-1)}(\hat{z}) < q_s.$$

Proof. See Appendix A.3.3. ☐

Panel II in Figure 4 illustrates this result. As the span of hard information η increases, the overlap between hard and soft fundamentals grows. Therefore fewer characteristics must be favorable for the "only-soft" fundamentals θ_s^s to be positive, and all else equal Bank B becomes more optimistic about θ_s^s. This implies that a lower soft signal suffices to induce the same level of expected quality $\hat{z}$, that is, $z_s^{s(-1)}(\hat{z};\eta,\alpha)$ decreases in η.

In contrast, as the precision α increases, the hard signal becomes more informative. Upon receiving a positive hard signal, Bank B is more certain that the "overlapping" characteristics covered by hard and soft information, that is, θ_s^h, are favorable. Since the soft signal s reflects $\theta_s \equiv \theta_s^h\theta_s^s$, Bank B updates its beliefs about θ_s^s downward. That is, a higher soft signal s is required to maintain the same expected quality of θ_s^s. Consequently, $z_s^{s(-1)}(\hat{z};\eta,\alpha)$ increases in α. This effect arises only when the hard and soft states are correlated; if $\eta = 0$, Bank B's beliefs about θ_s^s are independent of α.

3.2.3 Beliefs about Soft Signal upon Competition

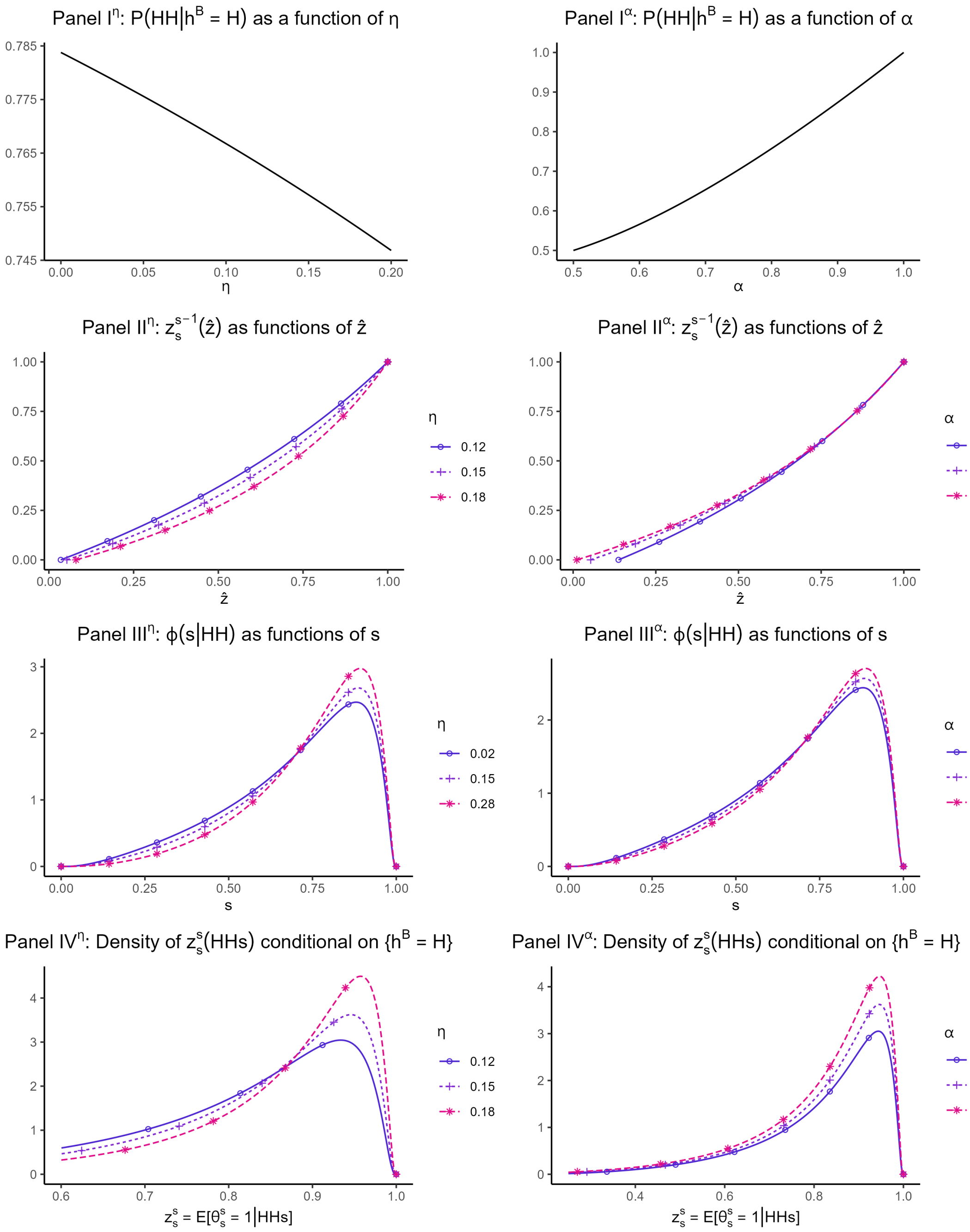
Finally, the strength of the Winner's Curse faced by Bank B upon competition depends on the distribution of the soft signals received by Bank A. This is captured by $\phi(s|HH)$ in (31), which represents the density of s conditional on two positive hard signals:

$$\phi(s|HH) = \phi(s) + \left[\frac{\eta q}{\frac{(1-\alpha)^2}{2\alpha-1} + q_h^h(1-\eta)}\right] \cdot [\phi_1(s) - \phi_0(s)]. \tag{32}$$

Here, $\phi(s)$ is the unconditional distribution of the soft signal s, and $\phi_{\theta_s}(s)$, which we derive in (7) and (8), is the distribution of s conditional on the realization of soft fundamental θ_s.

Lemma 5. ***(Conditional Distribution of the Soft Signal)*** *The distribution of the soft signal conditional on both lenders receiving a positive hard signal shifts to the right as the span and the precision of hard information increase. Formally, for soft signal below its prior mean* $s < q_s$*, we have*

$$\frac{d\phi(s|HH)}{d\eta} < 0 \quad \textit{and} \quad \frac{d\phi(s|HH)}{d\alpha} < 0.$$



Panel I^{η}: $P(HH|h^B = H)$ as a function of η

Panel I^{α}: $P(HH|h^B = H)$ as a function of α

Panel II^{η}: $z_s^{s-1}(\hat{z})$ as functions of $\hat{z}$

Panel II^{α}: $z_s^{s-1}(\hat{z})$ as functions of $\hat{z}$

Panel III^{η}: $\phi(s|HH)$ as functions of s

Panel III^{α}: $\phi(s|HH)$ as functions of s

Panel IV^{η}: Density of $z_s^s(HHs)$ conditional on $\{h^B = H\}$

Panel IV^{α}: Density of $z_s^s(HHs)$ conditional on $\{h^B = H\}$

Figure 4: **Conditional probability and density of posterior means of fundamentals.** Panel I^{η} and I^{α} depict $\mathbb{P}\left(HH|h^B = H\right)$ as functions of η and α. Panel II^{η} and II^{α} plots $s = z_s^{s-1}(\hat{z})$ as functions of $\hat{z}$, for three different levels of η and α respectively. Panel III^{η} and III^{α} depict the density of signal s conditional on $h^A = h^B = H$, and Panel IV^B_{η} and IV^B_{α} depict the density of posterior z_s^s. Baseline parameters: $\alpha = 0.8, \eta = 0.15, \tau = 1, q_h^h = 0.9$, and $q_s = 0.7$.

Proof. See Appendix A.3.4. $\square$

The lemma above shows that when both banks receive H, the realization of s is more likely to be higher as the span and precision of hard information increase. Panel III in Figure 4 illustrates this result. When the hard information broadens (η increases), the hard signal becomes informative about more soft fundamentals. Thus, when both hard signals are positive, it is more likely that θ_s is also positive, and the conditional distribution $\phi\left(s \mid HH\right)$ puts more weight on $\phi_1\left(s\right)$. Given the monotone likelihood ratio property, we know $\phi_1\left(s\right) - \phi_0\left(s\right) < 0$ for low values of s ($s < q_s$), implying that the soft signal is more likely to take higher values. Similarly, as the precision α increases, the hard signals provide a better assessment, including of the overlapping fundamentals in θ_s^h. This, in turn, makes it more likely for the soft fundamental to be positive upon HH.

It is worth emphasizing that the effects of η and α on $\phi\left(s \mid HH\right)$ do not explain the distinct impacts that span and precision have on the credit market (see Section 3.2.4). In fact, they resemble the effects of overall screening technology discussed in Section 3.1 and reflect the symmetric technological improvements for both lenders. Whether by increasing the correlation between the hard and soft signals (via greater span) or by making hard information "more public" (via higher precision), both dimensions raise the expected quality of the soft fundamentals upon competition.

3.2.4 Overall Effect

Although span and precision shift the conditional distribution of the soft signal under competition (and the overall screening efficiency) in the same direction (Section 3.2.3), they operate through distinct economic mechanisms. This distinction lies underneath the opposite effects of span and precision in the two previous sections ((Section 3.2.1 and 3.2.2), and highlights that Bank B is mostly concerned with the signal received by its opponent because it reveals information about θ_s^s, for which Bank B lacks private information. The following theorem formally states this result under mild conditions, with illustration given by Panel IV of Figure 4.

Theorem 1. ***(Span and Precision on Winner's Curse on Only-Soft State)*** *The span and precision of hard information have opposite effects on Bank B's perceived left tail of the distribution of* z_s^s. *Formally, for all* z *such that* $z_s^{s(-1)}(z) < q_s$, *we have*

$$\frac{d\mathbb{P}\left(z_s^s \leq z \mid h^B = H\right)}{d\eta} < 0, \quad \textit{while} \quad \frac{d\mathbb{P}\left(z_s^s \leq z \mid h^B = H\right)}{d\alpha} > 0 \textit{ if } q_s^s < \frac{2q_h - 1}{q_h^s\left(4q_h^h - 2q_h - 1\right)}.$$

Proof. See Appendix A.4. □

We need condition $q_s^s < \frac{2q_h - 1}{q_h^s\left(4q_h^h - 2q_h - 1\right)}$ in Theorem 1 to restrict the counterforce that a higher precision α associates competition with higher soft signal realizations; that is, shifts $\phi(s|HH)$ to the right. This shifting occurs through the correlated components of the hard and soft signal information, θ_s^h. When q_s^s is relatively small—specifically, below $\frac{2q_h-1}{q_h^s\left(4q_h^h-2q_h-1\right)}$—the only-soft state θ_s^s is more influential, as it spans a broader range of fundamentals. Since θ_s^s is unaffected by α, the impact of a greater α on the shift of the distribution of the soft signal (which reflects both θ_s^h and θ_s^s) tends to be muted when q_s^s is small.[13]

3.3 Bank Profits

Information technology, by affecting the severity of the information asymmetry between lenders, determines the competitiveness of the credit market. Following our findings in the previous section, we now show that the span and precision of information have opposite effects on the banks' equilibrium profits.

3.3.1 Information Span and Bank Profits

Despite an enlarged information span increasing the screening ability of both banks, it benefits Bank B relatively more than Bank A. In the proposition below, we show that an increase in the span η levels the playing field in the credit market.

Proposition 2. ***(Information Span on Equilibrium Profits)***

1. *The equilibrium profits of the non-specialized lender π^B are (weakly) increasing in η.*
2. *In the region of positive-weak equilibrium, the impact of η on Bank B's profits dominates that on Bank A's profits:*

$$\frac{d\pi^B}{d\eta} > \frac{d}{d\eta}\mathbb{E}\left[\pi^A\right]. \tag{33}$$

Proof. See Appendix A.5. ☐

There are two forces that affect Bank B's profits following an increase in span η. First, as discussed above, an increase in span increases the overlap between the hard and soft states and reduces the informational asymmetry among the banks. Second, Bank A, endowed with a more accurate screening technology, competes more aggressively for the borrower.

As suggested in the first part of Proposition 2 and illustrated in Figure 5, there exists a threshold $\hat{\eta}$ that delimits the zero- and positive-weak regions. When $\eta < \hat{\eta}$ the two effects

---

[13] To see this result, the coefficient in (32), which is $\frac{\eta q}{\frac{(1-\alpha)^2}{2\alpha-1}+q_h^h(1-\eta)}$, captures the magnitude of the shift. One can rewrite this coefficient as $\frac{\eta q_h}{\frac{(1-\alpha)^2}{2\alpha-1}+q_h} \cdot q_s^s$, which is increasing in q_s^s.

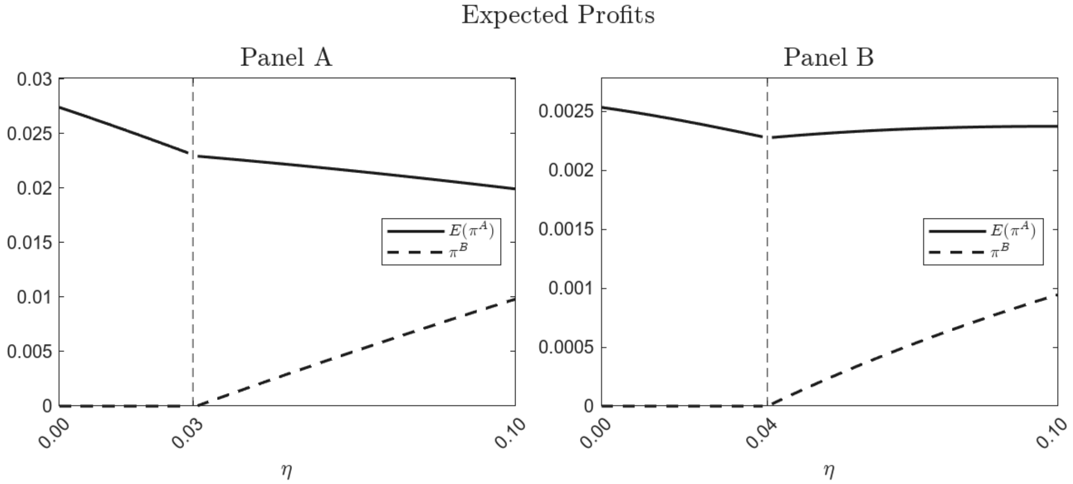


Figure 5: **Expected lender profits.** Panel A and Panel B plot expected lender profits against information span η under two sets of primitive parameters: Panel A, $\bar{r} = 0.36$, $q = 0.72$, $q_s = 0.9$, $\alpha_u = \alpha_d = \alpha = 0.7$, $\tau = 1$; Panel B, $\bar{r} = 0.33$, $q = 0.72$, $q_s = 0.9$, $\alpha_u = \alpha_d = \alpha = 0.6$, $\tau = 0.1$. The solid lines correspond to Bank A while the dashed lines correspond to Bank B.

exactly offset each other in equilibrium, and π^B stays at zero in the zero-weak equilibrium region. For $\eta > \hat{\eta}$, Bank A's informational advantage (and Bank B's Winner's Curse associated with it) shrinks to the extent that Bank A—when receiving a sufficiently low signal $s = \hat{s}$—loses its local monopoly power and becomes the break-even lender. In this case, the technological advancement dominates the increase in competition from the perspective of Bank B, who starts making positive profits in this positive-weak equilibrium.

Moreover, as the second part of Proposition 2 shows, in the region of positive-weak equilibria, the reduction in Bank A's informational advantage is evident in the behavior of the "profit gap" for the banks, which decreases with η. This result shows increasing the span levels the playing field, which we interpret as the credit market becoming more competitive.

Finally, while the information span η always helps Bank B (part 1 of Proposition 2), Bank A gains from improved screening too and hence its profits can also increase with η in the range of positive-weak equilibrium parameters ($\eta > \hat{\eta}$). Panel B in Figure 5 provides an example where Bank A's expected profits increase with η, whereas the opposite occurs in Panel A. Comparing the parameter configurations of the two panels in Figure 5, we find that $\mathbb{E}(\pi^A)$ is more likely to increase with η when the precision of signals—either τ for soft signal or α for hard signals—is low. For instance, when the precision of the soft signal τ is low, Bank A—initially holding a noisy signal about the soft state θ_s—gains more from the expanded span, as it reduces the uncertainty about θ_s considerably. In these settings, the benefits of improved screening outweigh the intensified competition from Bank B, leading to higher profits for Bank A. As we show in the welfare analysis in Section 3.4, this scenario may result in a Pareto improvement, with all agents in the economy enjoying greater surplus.

3.3.2 Information Precision and Bank Profits

The effect of an increase in the hard signal's precision α on equilibrium bank profits is quite involved, and in general, non-monotone. To understand the non-monotonicity, it is useful to consider two extreme cases. In an auction setting with asymmetric bidders, the uninformed bidder makes zero profit (Milgrom and Weber, 1982). When $\alpha = 0.5$ so that the hard signal is completely uninformative,[14] the model is identical to Milgrom and Weber (1982) where the uninformed lender B ignores the realization of h^B, randomizes its bids, and makes zero profits in equilibrium. On the other extreme, when $\alpha = 1$, hard information becomes public; and when $h^A = h^B = H$ we are back to Milgrom and Weber (1982) so that Bank B makes zero profits. In general, for values of $\alpha \in (0, 1)$, a positive-weak equilibrium (with $\pi^B > 0$) could arise, as shown in Panel D in Figure 6.

Hence, we show our formal results under restricted parameters. To focus on the contrast between span and precision, we set $\eta = 0$; this shuts down the improvement in the assessment of the overlapping characteristics θ_s^h when the precision increases. Providing a formal counterpart to Proposition 2, Proposition 3 shows that a higher precision benefits the specialized lender, Bank A.

Proposition 3. ***(Hard Signal Precision on Bank Profits.)*** *Suppose $\eta = 0$. In the range of zero-weak equilibrium, Bank A benefits more from a higher precision of hard signals; that is,*

$$\frac{d}{d\alpha}\mathbb{E}\left[\pi^A\right] > \frac{d\pi^B}{d\alpha} = 0. \tag{34}$$

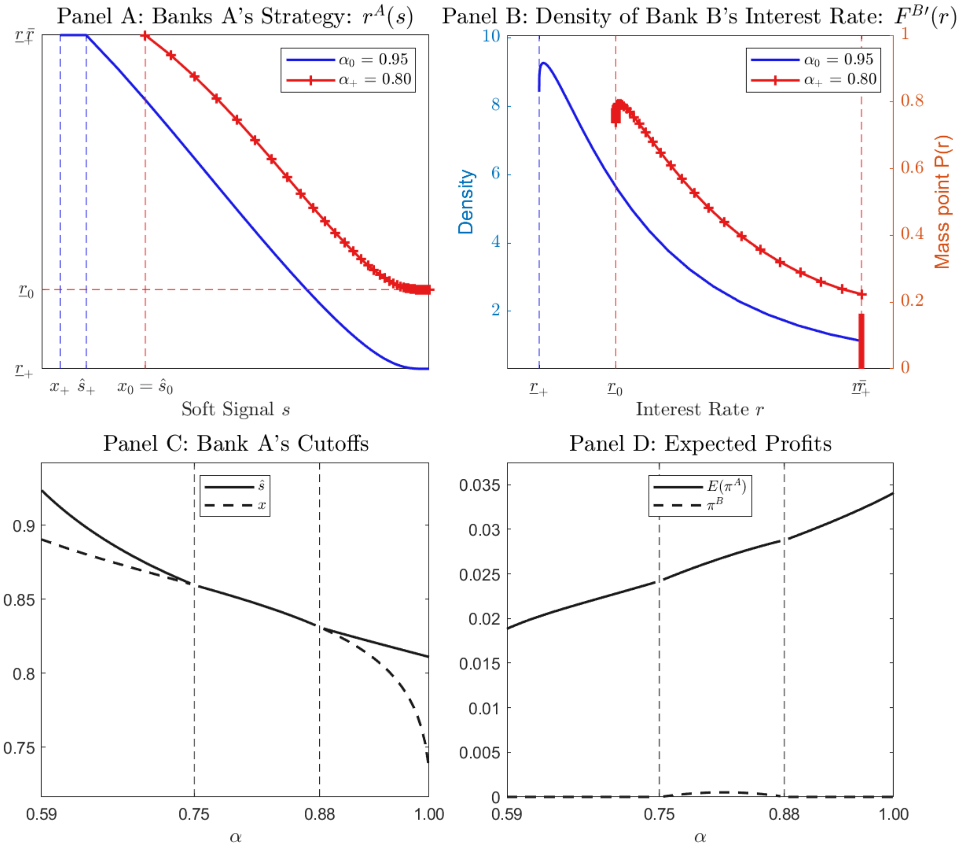
Proof. See Online Appendix B.4. ☐

Compared to Proposition 2, Proposition 3 concerns the region of zero-weak because we are interested in the scenario where α makes the specialized bank stronger. Under Assumption 2 (that is, $q_h > 0.5$), the more precise the hard signals, the more likely it is for lenders to compete ($h^A = h^B = H$) than to disagree and not compete ($h^A \neq h^B$). This tilt towards competition effectively increases the Winner's Curse that Bank B suffers from Bank A's soft signal. Hence, Bank A benefits more from increases in the hard signal precision, and its equilibrium profit improves.

Figure 6 plots the same equilibrium objects as Figure 2 (except $\eta = 0$ which is the case we focus on here), showing the comparative statics on α. First, Panels A and B illustrate

---

[14] Although this limiting case violates Assumption 1 which requires hard signals to be sufficiently strong, we have a well-defined equilibrium in this case a la Milgrom and Weber (1982) where both lenders ignore the hard signals.


Panel A: Banks A's Strategy: $r^A(s)$

Panel B: Density of Bank B's Interest Rate: $F^{B\prime}(r)$

Panel C: Bank A's Cutoffs

Panel D: Expected Profits

Figure 6: **Equilibrium strategies and profits for hard signal precision α.** Panel A depicts $r^A(s)$ as a function of s and Panel B plots $F^{B\prime}(r)$ as a function of r; strategies for $\alpha_+ = 0.8$ are depicted in red with markers while strategies with $\alpha_0 = 0.95$ are depicted in blue. Panel C depicts Bank A's thresholds $\hat{s} = \sup s^A(\bar{r})$ and $x = \sup s^A(\infty)$, and Panel D the expected profits for two lenders against α. Parameters: $\bar{r} = 0.36$, $q = 0.72$, $q_s = 0.9$, $\eta = 0$, and $\tau = 0.8$.

the lenders' equilibrium pricing strategies, showing that lenders set more aggressive rates (lower rates) for $\alpha_+ < \alpha_0$. When α increases from $\alpha_+ = 0.8$ to $\alpha_0 = 0.9$, both lenders are competing more fiercely by quoting lower interest rates, so the equilibrium turns from positive-weak to zero-weak (hence α_0 for the larger α). In Panel C, the cutoff strategies of Bank A generally decrease as α increases; this reflects the standard learning effect—Bank A, receiving a more accurate positive hard signal, withdraws at a worse soft signal. Notably, $\hat{s}$ and x coincide for mid-values of α, which is consistent with the non-monotonicity of π^B. Finally, Panel D illustrates that Bank A's expected profits increase with α in the region of zero-weak equilibrium, and that the non-specialized lender B's profits π^B are non-monotone in α with $\pi^B = 0$ at the two limiting cases of $\alpha = \frac{1}{2}$ or 1.

3.4 Credit Allocation and Welfare

We now analyze how information span affects credit allocation and welfare. After presenting some comparative statics on aggregate markers of credit market health as a function of η, we formally show that greater information span on hard signals always improves welfare.

3.4.1 Information Span on Credit Market Outcomes

We focus on three aggregate markers of credit market health: loan approval rates, non-performance rates, and the probability of funding good/bad borrowers. We also investigate the expected NPV of funded projects as a measure of total welfare in the banking sector.

Figure 7 shows the comparative statics of equilibrium outcomes as a function of the span of hard information η. Two forces drive these results. First, a higher η assesses more characteristics and reduces Type II mistakes, lowering the probability of receiving a positive hard signal. Second, it alleviates the Winner's Curse faced by Bank B, leading to more aggressive bidding and participation in equilibrium.

Panel A shows the expected loan approval rates for the two lenders. As η increases, Bank A's approval rate rises due to better screening and more aggressive participation. For Bank B, the approval rate (dashed line) depends on whether it earns zero or positive profits. All the discontinuous jumps in Figure 7 around $\hat{\eta} \approx 0.03$ correspond to equilibrium regime switching, as Bank B moves from random participation (when $\pi^B = 0$) to full participation upon receiving $h^B = H$ (when $\pi^B > 0$). In a zero-weak equilibrium, the relaxation of the Winners Curse makes Bank B more likely to compete, raising its approval rate. In a positive-weak equilibrium, Bank B already always participates, and the decline in approval rate reflects the reduced likelihood of a positive signal.

Panel B shows the non-performing rates of loans made by Bank A (solid line) and Bank B (dashed line). Within the same equilibrium category (zero-weak or positive-weak), both decrease with the information span η as improved the screening reduces Type II errors and increases average loan quality.

Panel C plots the probability of funding good (solid line) and bad (dashed line) borrowers. As a larger η represents a better screening technology, one would expect the probability of funding good loans to rise while that of bad loans to fall. This is indeed the case in Panel C when the equilibrium is in the positive-weak regime for $\eta > \hat{\eta} \approx 0.03$. However, in the zero-weak regime ($\eta < \hat{\eta} \approx 0.03$), a larger span attenuates the Winner's Curse and Bank B competes more aggressively, thereby extending more loans regardless of borrower types when the span increases.

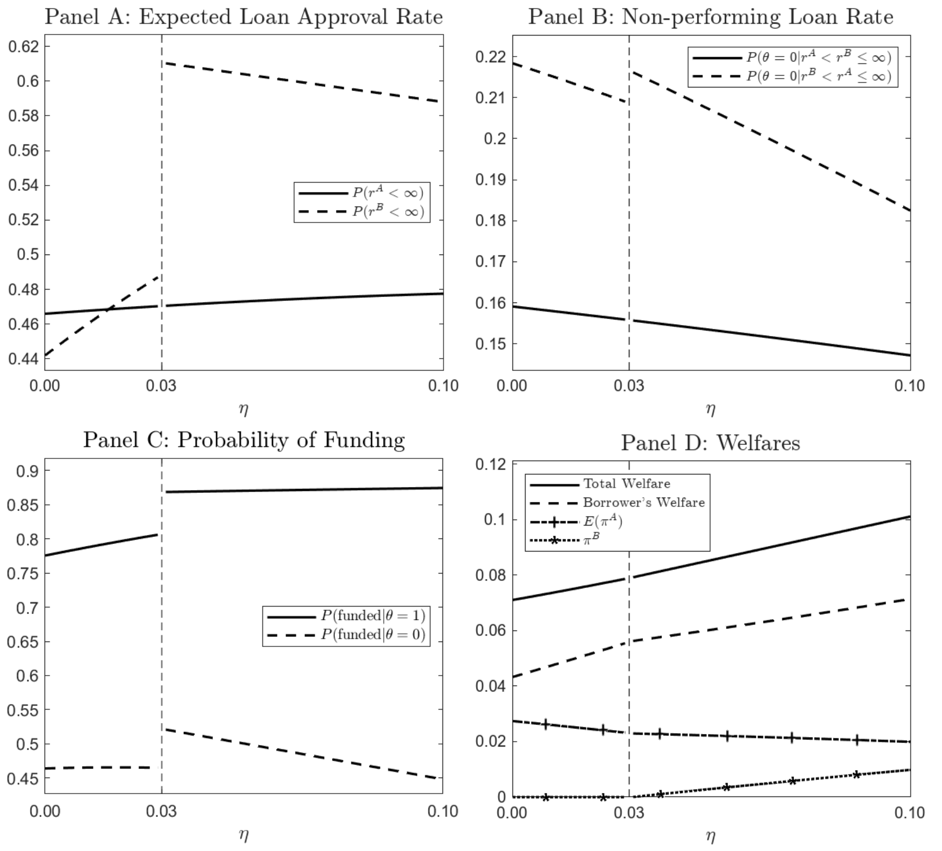


Figure 7: **Credit allocation and welfare.** Panel A and Panel B show the expected loan approval and non-performing rates, respectively. The solid lines correspond to Bank A while the dashed lines correspond to Bank B. Panel C depicts the probability of getting funded for a high-quality borrower (solid line) and a low-quality borrower (dashed line). Panel D illustrates aggregate welfare (solid line), borrower surplus (dashed line), and lenders' expected profits (dash-dotted line with cross markers for A while dotted line with star markers for B). All variables are depicted as a function of the span of hard information η. Priors q_h, q_s^s and information span η satisfy $q_h = q/q_s \cdot (1-\eta)$ and $q_s^s = q_s/(1-\eta)$. Parameters: $\bar{r} = 0.36$, $q = 0.72$, $q_s = 0.9$, $\tau = 1$ (top two panels) and $\alpha_u = \alpha_d = \alpha = 0.7$ (bottom two panels).

3.4.2 Information Span and Welfare

The proposition below shows that total welfare increases with the span of hard information.

Proposition 4. *Total welfare, measured as expected net present value (NPV) of funded projects, strictly increases in information span η.*

Proof. See Online Appendix B.5. □

Panel D shows how aggregate welfare and individual surpluses respond to increases in the information span η. As η rises, screening and lender participation improve: Bank A lowers its soft signal threshold $x(\eta)$, and Bank B exits less often ($F^B(\bar{r}; \eta)$ increases).

While better screening always raises total welfare, the effect of increased participation depends on the marginal borrowers efficiency. In the *positive-weak* equilibrium, greater Bank

A participation reduces welfare. Bank A breaks even at $s = x(\eta)$—gains from competition with Bank B (HH) but loses when it lends alone (HL). Since HH gains are mere transfers, total welfare declines. In the *zero-weak* equilibrium, there is no competition from Bank B upon HH, so Bank A's marginal lending coincides with the planner's and is welfare-neutral.

Despite the potential counterforce on efficiency due to endogenous participation, we show that the improved screening always dominates in both regimes, and aggregate welfare rises with η. Note that welfare remains continuous at the zero-to-positive-weak transition in Panel D: although loan quantity jumps, added loans yield zero NPV on average since both Bank B and borrowers break even at the cap rate $\overline{r}$.

Panel D in Figure 7 shows that in a zero-weak equilibrium under $\eta < \hat{\eta} \approx 0.03$, all welfare gains accrue to borrowers via a transfer from banks; while in a positive-weak equilibrium under $\eta > \hat{\eta}$, Bank B also gains from increased η. That is, all agents benefit from higher η, except Bank A in the positive-weak region. Yet, as demonstrated by Panel B in Figure 5, even Bank A could benefit when signal precision is low. In sum, broadening hard information—via modern data technology—can lead to a Pareto improvement.

4 Model Extensions

This section considers two extensions to our baseline model. First, we allow for correlated hard signals, motivated by open banking initiatives. Second, we consider an alternative modeling of hardening soft information by introducing a signal on θ_s^h, and show that both the equilibrium characterization and the key economic takeaways are robust to this alternative.

4.1 Correlated Hard Signals

A well-recognized consequence of advances in information technology is the increased correlation of hard information across lenders. For instance, open banking initiatives—by allowing customer-authorized data sharing—make lenders assessments more aligned (He, Huang, and Zhou, 2023; Babina, Buchak, De Marco, Foulis, Gornall, Mazzola, and Yu, forthcoming). We extend our model to capture this effect and show that increasing signal correlation, or making information more public, also features distinct implications for credit market equilibrium compared to the increase in information span.

We modify the hard information technology as follows. Suppose that, with probability $\rho_h \in [0, 1]$, lenders receive the same binary signal realization $h^c \in \{H, L\}$, while with probability $1 - \rho_h$ each lender receives an independent binary hard signal (just like our baseline). We solve this extension in Online Appendix B.6 and plot the comparative statics with re-

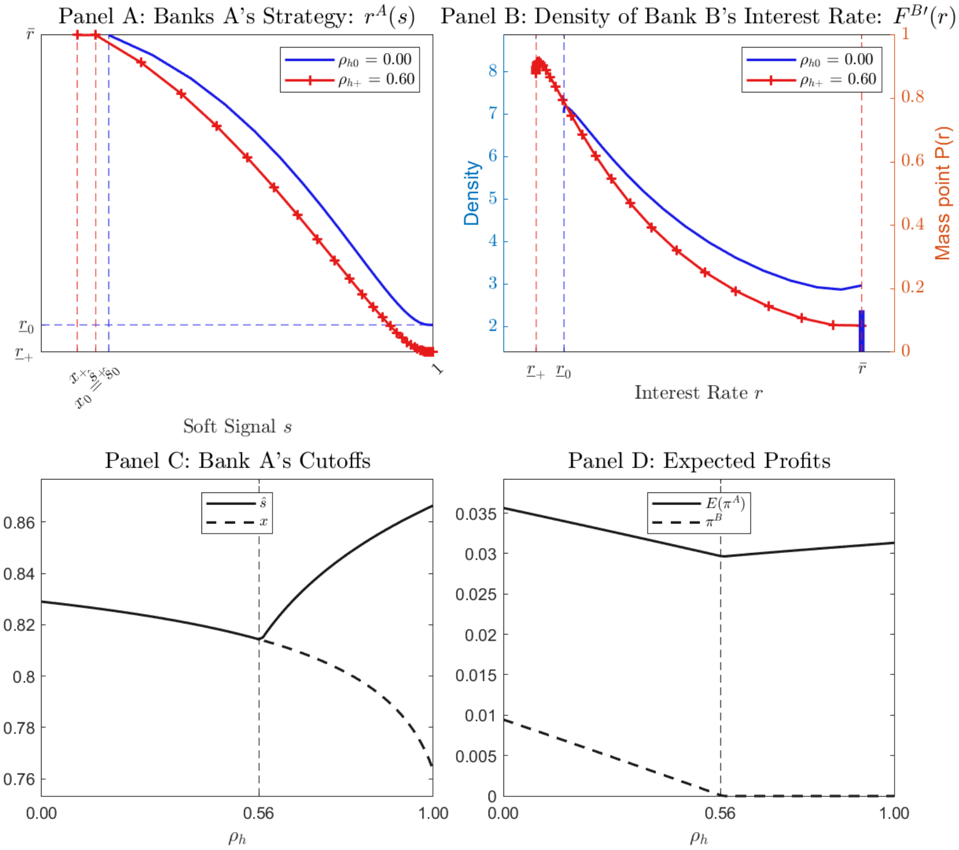


Figure 8: **Equilibrium strategies and profits for hard signal correlation ρ_h.** Panel A depicts $r^A(s)$ as a function of s and Panel B plots $F^{B\prime}(r)$ as a function of r; strategies for $\rho_{h+} = 0.6$ (a positive-weak equilibrium) are depicted in red with markers while strategies with $\rho_{h0} = 0$ (a zero-weak equilibrium) are depicted in blue. Panel C depicts Bank A's thresholds $\hat{s} = \sup s^A(\bar{r})$ and $x = \sup s^A(\infty)$, and Panel D depicts the expected profits for two lenders, both as a function of ρ_h. Parameters: $\bar{r} = 0.45$, $q_h = 0.8$, $q_s = 0.9$, $\eta = 0$, $\alpha = 0.7$, and $\tau = 1$.

spect to the correlation $\rho_h \in [0, 1]$ of hard signals across two lenders in Figure 8. The bottom two panels show that a larger ρ_h makes a zero-weak equilibrium more likely. In the extreme case in which $\rho_h = 1$, the hard signal becomes a public signal; then Bank B becomes effectively uninformed, ending up with zero profits (Milgrom and Weber, 1982). It is therefore interesting to observe that the economic implications of ρ_h, which typically increases with data sharing, are qualitatively similar to those of greater signal precision but opposite to the effects of increasing information span (see the discussion in Section 3.3).

4.2 Additional Hard Signals on θ_s^h

In our analysis, we interpret the increase in the span of hard information as the outcome of "hardening" soft information, allowing hard signals to cover a broader range of fundamental states. Alternatively, one could introduce an additional signal about θ_s^h that is available to both banks, without altering the structure of the existing signals.

Consider an environment before soft information is hardened, so that $\eta = 0$. Suppose Big Data technology now covers the overlapping fundamental state θ_h^s as in (3). Let $h_s^j \in \{H, L\}$ denote lender j's binary signal of θ_h^s, which we refer to as the hardened soft signal. For tractability, we assume that these signals are also decisive as in Section 1.2.3, so that each lender rejects the borrower as long as $h_s^j = L$. And, as in Section 4.1, any correlation ρ_s^h between the two hardened soft signals can be allowed (see details in Online Appendix B.7). Here, we focus on the extreme case $\rho_s^h = 1$, so that both banks receive the same signal $h_s^A = h_s^B = h_s^c$. Let α^s be the precision of h_s^c; that is, $h_s^c = H$ ($h_s^c = L$) with probability $\alpha_s \in (\frac{1}{2}, 1)$ conditional on $\theta_s^h = 1$ ($\theta_s^h = 0$).

This "public" hardened soft signal captures the rising correlation correlation in signals generated by Big Data technology in a stark way,[15] leading to a simpler analysis. As competition occurs only when $h_s^c = H$, the relevant soft signal distribution becomes $\phi\left(s \mid h_s^c = H\right)$. Online Appendix B.7 shows that, once distributions are replaced by those conditional on $h_s^c = H$, the model is isomorphic (up to a constant) to the $\eta = 0$ case with independent fundamentals and signals. This equivalence allows us to fully characterize the credit market equilibrium in this alternative setting.

We draw two key insights from the resulting credit market equilibrium. First, adding a signal on θ_s^h—analogous to expanding the span of the hard signal—can level the playing field in credit markets with asymmetric lenders. This is most evident in the extreme case where $\theta_s^h = \theta_s$ (so $\theta_s^s = 1$ and there is no only-soft state) and $\alpha_s = 1$ (so a perfect precision for the additional signal), under which the hardened soft signal reveals the soft fundamental fully. In this scenario, Big Data technology eliminates Bank A's information advantage, which is equivalent to the symmetric-lender setting analyzed by Broecker (1990).

However, under more general parameters, the two modeling approaches can have different economic implications. This leads to our second, and arguably more important, point: just as the main insight of this paper, we show that in the alternative modeling the comparative statics with respect to the precision of the hardened soft signal (α_s) differ from those with respect to the information span η in our baseline model.

To see this, suppose that θ_s^h covers only a small subset of the soft fundamental states θ_s, so that the residual uncertainty about the only-soft states θ_s^s remains substantial. In Online Appendix B.7, we show that the comparative statics of α_s share the same sign as α (rather than η), particularly for the three effects analyzed in Section 3.2. For example, consider Bank B's inference about θ_s^s. As in Section 3.2.2, when Bank B receives a positive $h_s^B = H$

---

[15] In fact, $\rho_s^h = 1$ endogenously arises when the precision of the hardened soft signal becomes perfect ($\alpha_s \to 1$): when h_s^j reveals θ_s^h perfectly, h_s^j's must be the same across two lenders.

and competes against an opponent with soft signal s, a more precise h_s^B about θ_s^h leads it to update its belief about θ_s^s downward, thereby exacerbating the Winner's Curse due to residual uncertainty. Conceptually, this is because the precision of the hardened soft signal α_s functions in the same way as the precision of the hard signal α.

5 Concluding Remarks

One of the main roles of banks in the economy is to produce information for allocating credit. In this paper, we show that the nature of a bank's information technology—specifically, the distinction between the *span* and *precision* of hard information—shapes the credit market equilibrium and the intensity of competition. One of our main contributions is to formalize the concept of information span, defined as the breadth of fundamentals covered by signals. While both span and precision improve screening and thus allocative efficiency, we show that they have opposing effects on the residual uncertainty (faced by the weaker lender), the strategic interactions, and market competitiveness.

At first glance, advances in information technology should benefit all lenders—including both specialized institutions and emerging fintechs. Indeed, large banks have led IT investments in recent years (He, Jiang, Xu, and Yin, 2025). Yet, the growing empirical literature on fintechs (e.g., Berg, Fuster, and Puri, 2022) suggests that new technologies have allowed less-established lenders to catch up, intensifying competition in the credit market.

Motivated by this empirical evidence, we develop a model with *asymmetric* lenders and *symmetric* technological improvements to analyze how expanding the information span (of hard information)—particularly through hardening of soft information—affects the equilibrium in the credit market. Our model highlights the crucial difference between information span, which captures the "breadth" of information, and the precision of information, which captures its "quality." This difference is essential for understanding the above-mentioned empirical observation that technological change related to data gathering and processing has often favored non-specialized entrants. In fact, while greater precision tends to reinforce the advantage of specialized lenders, a broader information span levels the playing field.

More broadly, our results suggest that the *type* of technological progress in information processing—whether it improves span, precision, or public availability—matters for the structure and efficiency of credit markets. By making this distinction explicit, we provide a framework for evaluating recent and ongoing changes in financial data infrastructures and their implications for competition, access to credit, and welfare.

A Technical Appendices

A.1 Outline of Proof for Proposition 1

There are four parts of the proof: 1) showing monotonicity of $r^A(\cdot)$; 2) solving for equilibrium Bank B strategy $F^B(r)$; 3) solving for π^B and $(\hat{s}, x)$; and 4) global optimality of Bank A's strategy $r^A(\cdot)$. For details in see Online Appendix B.2, though we provide derivations for the FOCs in Eq. (23) and (24). Bank A's profits in (15) can be expressed as a function of $Q^A(r;s)$:

$$\pi^A(r, s) = Q^A(r;s) \cdot (1+r) - \left[p_{HH}(s)\left(1 - F^B(r)\right) + p_{HL}(s)\right].$$

Taking derivative with respect to r and noticing $\frac{Q^{A\prime}(r;s)}{\mu_{HH}(s)} = -p_{HH}(s)F^{B\prime}(r)$, we arrive at the equation (23). Similarly, for Bank B, we can write its objective (16) as

$$\pi^B(r) = Q^B(r) \cdot (1+r) - \left(\int_0^{s^A(r)} p_{HH}(t)dt + \overline{p}_{LH} r\right).$$

Taking derivative w.r.t. r and noticing that $\frac{Q^{B\prime}(r)}{\mu_{HH}(s^A(r))} = p_{HH}(s^A(r))s^{A\prime}(r)$, we arrive at the equation (24).

A.2 Proof of Lemma 2

Proof. Note that

$$z(H;\alpha,\eta) \equiv \mathbb{E}\left[\theta = 1 \middle| h^j = H\right] = \frac{\mathbb{P}\left(\theta = 1, h^j = H\right)}{\mathbb{P}(h^j = H)} = \frac{q\alpha}{1 - \alpha + q_h^h(1-\eta)(2\alpha - 1)},$$

which is strictly increasing in information span η since $\alpha > 0.5$. For signal precision α, we rewrite

$$z(H;\alpha) = \frac{q}{\underbrace{\left[1 - q_h^h(1-\eta)\right]}_{+} \underbrace{\frac{1-\alpha}{\alpha}}_{\downarrow \text{ in } \alpha} + q_h^h(1-\eta)}.$$

The denominator strictly increases in $\frac{1-\alpha}{\alpha}$ and decreases in α. Therefore, $z(H;\alpha)$ strictly increases in α. ☐

A.3 Bank B' Beliefs upon $h^B = H$

A.3.1 Derivation of z_s^s

We first calculate $p_{HH}(s)$ here which will be used below,

$$p_{HH}(s) = \underbrace{q\alpha^2\phi_1(s)}_{\theta=1} + \underbrace{\left(1 - q_h^h\right)(1-\alpha)^2\phi(s)}_{\theta_h^h=0} + \underbrace{\left[(1-q_s)\alpha^2 - \eta(2\alpha - 1)\right]q_h^h\phi_0(s)}_{\theta_h^h=1,\theta_s=0}. \tag{35}$$

Eq. (35) calculates the probability of HHs depending on different realizations of θ_h^h, θ_s^h and θ_s^s. The third term for the joint probability for $\theta_h^h = 1$, $\theta_s = 0$ and HHs is $q_h^h\left[q_h^s\alpha^2(1-q_s^s) + (1-q_h^s)(1-\alpha)^2\right]\phi_0(s) =$

$\left[(1-q_s)\,\alpha^2-\eta\,(2\alpha-1)\right] q_h^h\phi_0\,(s)\,.$

The posterior mean of θ_s^s conditional on $\left\{h^A=h^B=H,s\right\}$, can be calculated as

$$\begin{aligned} z_s^s\,(s)\equiv\mathbb{E}\left[\theta_s^s\middle|\,h^A=h^B=H,s\right]&=\frac{\mathbb{P}\left(\theta_s^s=1,h^A=h^B=H,s\right)}{p_{HH}\,(s)}\\ &=\frac{\left[q_h^h\alpha^2+\left(1-q_h^h\right)(1-\alpha)^2\right]\cdot q_s^hq_s^s\phi_1\,(s)+q_s^s\left(1-q_s^h\right)(1-\alpha)^2\,\phi_0\,(s)}{p_{HH}(s)}. \end{aligned} \tag{36}$$

It is easy to check that $z_s^s\,(s)$ is strictly increasing in s as

$$z_s^s(s)=\frac{1}{1+\frac{\frac{1-q_s^s}{1-q_s}\cdot\overline{p}_{HH}}{\left[q_h^h\alpha^2+\left(1-q_h^h\right)(1-\alpha)^2\right]\cdot\underbrace{\frac{s}{1-s}}_{\uparrow\text{ in }\alpha}+\frac{q_s^s\left(1-q_s^h\right)}{1-q_s}(1-\alpha)^2}}.$$

Note that $\mathbb{P}\left(z_s^s\,(s)\in(z,z+dz)\right)=\mathbb{P}\left(HH,s\in\left(z_s^{s-1}\,(z)\,,z_s^{s-1}\,(z)+dz_s^s\,(s)\right)\right)$. Then the density of $z_s^s(s)$ is

$$p_{HH}\left(z_s^{s-1}\,(z)\right)\frac{1}{z_s^{s\prime}\left(z_s^{s-1}\,(z)\right)}dz.$$

A.3.2 Proof of Lemma 3

Proof. The probability of competition upon $h^B=H$ is

$$\mathbb{P}\left(HH\middle|\,h^B=H;\eta,\alpha\right)=\frac{q_h\,(\eta)\,\alpha^2+(1-q_h\,(\eta))\,(1-\alpha)^2}{q_h\,(\eta)\,\alpha+(1-q_h\,(\eta))\,(1-\alpha)}, \tag{37}$$

where $q_h(\eta)=q_h^h(1-\eta)$ is a function of η. One can rewrite the expression as

$$\mathbb{P}\left(HH\middle|\,h^B=H;\eta\right)=\frac{\frac{(1-\alpha)^2}{q_h^h(2\alpha-1)}+1-\eta}{\frac{1-\alpha}{q_h^h(2\alpha-1)}+1-\eta}=1-\underbrace{\frac{(1-\alpha)\,\alpha}{q_h^h\,(2\alpha-1)}}_{>0,\text{ as }\alpha\in(\frac{1}{2},1)}\frac{1}{\frac{1-\alpha}{q_h^h(2\alpha-1)}+1-\eta}.$$

Since $\alpha\in(\frac{1}{2},1)$, it is clear from this expression that $\mathbb{P}\left(HH\middle|\,h^B=H;\eta\right)$ is strictly decreasing in η.

For the monotonicity in α, one can show that

$$\operatorname{sgn}\left[\frac{\partial\mathbb{P}\left(HH\middle|\,h^B=H;\alpha\right)}{\partial\alpha}\right]=\operatorname{sgn}\left[q_h+2q_h\left(\alpha^2-\alpha\right)-(1-\alpha)^2\right].$$

The key term $M(\alpha)\equiv q_h+2q_h\left(\alpha^2-\alpha\right)-(1-\alpha)^2$ is strictly increasing in α for $\alpha\in(\frac{1}{2},1)$, since $M'(\alpha)=2q_h(2\alpha-1)+2(1-\alpha)>0$. Hence, for $\alpha\in(\frac{1}{2},1)$,

$$M(\alpha)\geq M(\frac{1}{2})=\frac{q_h}{2}-\frac{1}{4}>0,$$

where the last inequality follows from Assumption 2. Therefore, $\frac{\partial \mathbb{P}\left(HH|h^B=H;\alpha\right)}{\partial \alpha} > 0$. ☐

A.3.3 Proof of Lemma 4

Proof. Recall $s = z_s^{s(-1)}(z;\eta,\alpha)$ is the soft signal realization at which $z_s^s = z$. As discussed after Eq. (36), $z_s^s(s;\eta,\alpha)$ strictly increases in s. It remains to check the monotonicity of $z_s^s(s;\eta,\alpha)$ in η and α.

Using the definition of z_s^s in (36) and the expression of $p_{HH}(s)$ in (35), we have

$$z_s^s(s;\eta) = \frac{\left[q_h^h\alpha^2 + \left(1-q_h^h\right)(1-\alpha)^2\right]\cdot q_s\phi_1(s) + \left(\frac{q_s}{1-\eta} - q_s\right)(1-\alpha)^2\phi_0(s)}{q\alpha^2\phi_1(s) + \left(1-q_h^h\right)(1-\alpha)^2\phi(s) + \left[(1-q_s)\alpha^2 - \eta(2\alpha-1)\right]q_h^h\phi_0(s)},$$

where we have used $q_s^h(\eta) = 1-\eta$, $q_s^s(\eta) = \frac{q_s}{1-\eta}$. It is easy to check that the numerator increases in η be good) and the denominator $p_{HH}(s)$ decreases in η since $\alpha > \frac{1}{2}$. Therefore, when η increases, $z_s^s(s;\eta)$ becomes larger and we need a lower $s = z_s^{s(-1)}(z;\eta)$ to keep at the same threshold $z_s^s = z$.

For α, we rewrite $z_s^s(s;\alpha)$ in (36) as a function of $x = \frac{\alpha^2}{(1-\alpha)^2}$ (which increases in α):

$$\begin{aligned} z_s^s\left(s;x(\alpha) = \frac{\alpha^2}{(1-\alpha)^2}\right) =& \frac{\overbrace{\left[q_h^h x + \left(1-q_h^h\right)\right]\cdot q_s^h q_s^s\phi_1(s) + q_s^s\left(1-q_s^h\right)\phi_0(s)}^{H(x)}}{\left[q_h^h x + \left(1-q_h^h\right)\right]q_s^h q_s^s\phi_1(s) + \underbrace{\left[q_h x + (1-q_h)\right]\left(1-q_s^s\right)\phi_0(s)}_{G(x)} + q_s^s\left(1-q_s^h\right)\phi_0(s)} \\ =& \frac{H(x)}{H(x)+G(x)}, \end{aligned}$$

where $H(x) \equiv \left[q_h^h x + \left(1-q_h^h\right)\right]q_s^h q_s^s\phi_1(s) + q_s^s\left(1-q_s^h\right)\phi_0(s)$ and $G(x) \equiv \left[q_h x + (1-q_h)\right]\left(1-q_s^s\right)\phi_0(s)$. Then

$$\frac{\partial z_s^s(s;x)}{\partial x} = \frac{q\phi_1(s)G(x) - q_h\left(1-q_s^s\right)\phi_0(s)H(x)}{\left(H(x)+G(x)\right)^2} = \frac{q\left(1-q_s^h\right)\left(1-q_s^s\right)\phi_0(s)\left[\phi_1(s)-\phi_0(s)\right]}{\left(H(x)+G(x)\right)^2} < 0. \quad (38)$$

When $s < q_s$, $\phi_1(s) - \phi_0(s) = \left(\frac{s}{q_s} - \frac{1-s}{1-q_s}\right)\phi(s) < 0$, and the inequality follows. Hence, $z_s^s(s;x(\alpha))$ strictly decreases in $x(\alpha) = \frac{\alpha^2}{(1-\alpha)^2}$ which implies that $z_s^s(s;\alpha)$ strictly decreases in α. Since $z_s^s(s;\alpha)$ is strictly increasing in s, we need a higher s to keep $z_s^s = z$, i.e., $s = z_s^{s(-1)}(z;\alpha)$ strictly increases in α when $s < q_s$.

☐

A.3.4 Proof of Lemma 5

Proof. Using $p_{HH}(s)$ in Eq. (35) and $\overline{p}_{HH} = q_h(\eta)\alpha^2 + (1-q_h(\eta))(1-\alpha)^2$, one can calculate

$$\phi(s\,|HH;\eta,\alpha) = \frac{p_{HH}(s)}{\overline{p}_{HH}} = \phi(s) + \underbrace{\left[\frac{\eta q}{\frac{(1-\alpha)^2}{2\alpha-1} + q_h^h(1-\eta)}\right]}_{\uparrow \text{ in } \eta, \uparrow \text{ in } \alpha}\cdot\underbrace{\left[\phi_1(s)-\phi_0(s)\right]}_{<0 \text{ iff } s<q_s}$$

It is easy to check that the first bracketed term $\frac{\eta q}{\frac{(1-\alpha)^2}{2\alpha-1}+q_h^h(1-\eta)}$ strictly increases in η when $\alpha > \frac{1}{2}$. This term is also strictly increasing in α since $\frac{d\left[\frac{(1-\alpha)^2}{2\alpha-1}\right]}{d\alpha} < 0$. When $s < q_s$, the second bracketed term $\phi_1(s) - \phi_0(s) = \frac{s}{q_s}\phi(s) - \frac{1-s}{1-q_s}\phi(s) < 0$. Therefore, when $s < q_s$, $\phi(s\,|HH;\eta,\alpha)$ is strictly decreasing in both η and α. ☐

A.4 Proof of Theorem 1

Proof. The left tail event of interest is given in Eq. (31), which we replicate here:

$$\mathbb{P}\left(z_s^s \le z|\, h^B = H\right) = \int_0^{s=z_s^{s(-1)}(z;\eta,\alpha)} \frac{p_{HH}(t;\eta,\alpha)}{\mathbb{P}(h^B = H;\eta,\alpha)}dt. \tag{39}$$

Part 1: the effect of η. From Lemma 4, the upper integration limit $s = z_s^{s(-1)}(z;\eta)$ of (39) is strictly decreasing in η. We decompose the integrand into

$$\frac{p_{HH}(s)}{\mathbb{P}(h^B = H)} = \mathbb{P}\left(HH|\, h^B = H\right)\cdot \phi(s\,|HH).$$

Lemma 3 shows that $\mathbb{P}\left(HH|\, h^B = H;\eta\right)$ strictly decreases in η, and Lemma 5 shows that when $s < q_s$, the second term $\phi(s\,|HH;\eta)$ also strictly decreases in η. Taken together, (39) strictly decreases in η.

Part 2: The effect of α. From Lemma 4, the upper integration limit $s = z_s^{s(-1)}(z;\alpha)$ in (39) is strictly increasing in α when $s < q_s$. Now we show that the integrand in (39), $\frac{p_{HH}(t;\alpha)}{\mathbb{P}(h^B=H;\alpha)}$, is strictly increasing in α under condition $q_s \le \frac{2q_h-1}{4q_h^h-2q_h-1}$. Let $N(\alpha) \equiv p_{HH}(t)$, which is given in Eq. (35), and $D(\alpha) \equiv \mathbb{P}(h^B = H) = q_h\alpha + (1-q_h)(1-\alpha)$ denote the numerator and denominator of $\frac{p_{HH}(t;\alpha)}{\mathbb{P}(h^B=H;\alpha)}$ respectively. Then

$$\operatorname{sgn}\left\{\frac{\partial\frac{p_{HH}(t;\alpha)}{\mathbb{P}(h^B=H;\alpha)}}{\partial\alpha}\right\} = \operatorname{sgn}\{N'D - D'N\} = \operatorname{sgn}\left\{\left[1 - \frac{\left(1-q_s^h\right)}{1-q_s}(1-t)\right]q_h^h - 1 + (2q_h-1)\alpha^2 + 2(1-q_h)\alpha\right\}. \tag{40}$$

Let $M(\alpha,t) \equiv \left[1 - \frac{\left(1-q_s^h\right)}{1-q_s}(1-t)\right]q_h^h - 1 + (2q_h-1)\alpha^2 + 2(1-q_h)\alpha$. Note that

$$\frac{\partial M(\alpha,t)}{\partial\alpha} > 0, \quad \frac{\partial M(\alpha,t)}{\partial t} > 0.$$

Then the minimum value of $M(\alpha,t)$ is when $\alpha = \frac{1}{2}$ and $s = 0$:

$$M(\alpha,t) \ge M\left(\alpha = \frac{1}{2}, t = 0\right) = -\frac{\left(1-q_s^h\right)q_h^h}{1-q_s} + q_h^h - \frac{2q_h+1}{4}.$$

Note that $q_h^h - \frac{2q_h+1}{4} \ge q_h - \frac{2q_h+1}{4} = \frac{2q_h-1}{4} > 0$ where the first inequality uses $q_h^h \ge q_h$ and the last inequality uses $q_h > \frac{1}{2}$. Then

$$q_s \le \frac{2q_h-1}{4q_h^h-2q_h-1} \Leftrightarrow M\left(\frac{1}{2},0\right) \ge 0 \Rightarrow M(\alpha,t) \ge M\left(\alpha = \frac{1}{2}, s = 0\right) \ge 0.$$

Therefore, if $q_s \leq \frac{2q_h-1}{4q_h^h-2q_h-1}$, the integrand $\frac{p_{HH}(t)}{\mathbb{P}(h^B=H)}$ of (39) increases in α because the sign of derivative is determined by $M(\alpha,t) \geq 0$ (see Eq.(40)).

Taken together, the left tail event of interest in (39) strictly increases in α if $q_s \leq \frac{2q_h-1}{4q_h^h-2q_h-1}$.

□

A.5 Proof of Proposition 2

Lemma 6. *Define the function*

$$\Delta\pi(s) \equiv \pi^A(r^A(s),s) - \phi_1(s)\pi^B(r^A(s)). \tag{41}$$

Then the expected difference in lender profits can be expressed as

$$\mathbb{E}(\pi^A) - \pi^B = \begin{cases} \displaystyle\int_{\hat{s}}^1 \Delta\pi(s)\,ds - \int_0^x \phi_1(s)\pi^B\,ds, & \textit{if } \pi^B > 0, \\ \displaystyle\int_{\hat{s}}^1 \Delta\pi(s)\,ds + \int_x^{\hat{s}} \pi^A(s,\overline{r})\,ds, & \textit{if } \pi^B = 0. \end{cases} \tag{42}$$

The first term for $s \geq \hat{s}$ is driven by the difference in lending costs $C^j(s)$ where $j \in \{A,B\}$,

$$\Delta\pi(s) = -\underbrace{\left[\int_0^s \phi_1(t)\,dt \cdot p_{HH}(s) + p_{HL}(s)\right]}_{C^A(s)} + \underbrace{\phi_1(s)\left[\int_0^s p_{HH}(t)\,dt + \overline{p}_{LH}\right]}_{C^B(s)}. \tag{43}$$

Proof. See Online Appendix B.3.1. □

Lemma 7. *The break-even soft signals s_A^{be} and s_B^{be} defined in Eq. (55) and (53) satisfy*

$$\frac{\partial s_A^{be}}{\partial\eta} < 0, \quad \frac{\partial s_B^{be}}{\partial\eta} < 0.$$

Proof. See Online Appendix B.3.2. □

Proof of Proposition 2

Proof. From Lemma 6, the equilibrium profit gap between lenders is given by

$$\mathbb{E}(\pi^A) - \pi^B = \begin{cases} \int_{\hat{s}}^1 \Delta\pi(s)\,ds - \int_0^x \phi_1(s)\pi^B\,ds, & \text{if } \pi^B > 0, \\ \displaystyle\int_{\hat{s}}^1 \Delta\pi(s)\,ds + \int_x^{\hat{s}} \pi^A(s,\overline{r})\,ds, & \text{if } \pi^B = 0. \end{cases} \tag{44}$$

Step 1. We show that for $s \geq \hat{s}$, the profit gap $\int_{\hat{s}}^1 \Delta\pi(s)\,ds$ strictly decreases in η. In fact, we show the stronger claim that for any $s \geq \hat{s}$, we have $\frac{d\Delta\pi(s;\eta)}{d\eta} > 0$. From Lemma 6, when $s \geq \hat{s}$ and $r^A(s) \in [\underline{r},\overline{r})$, lenders' profit gap is determined by the difference in lending costs

$$\Delta\pi(s;\eta) = -\underbrace{\left[\int_0^s \phi_1(t)\,dt \cdot p_{HH}(s;\eta) + p_{HL}(s)\right]}_{C^A(s)} + \underbrace{\phi_1(s)\left[\int_0^s p_{HH}(t;\eta)\,dt + \overline{p}_{LH}\right]}_{C^B(s)}. \tag{45}$$

Moreover, information span η does not affect lending costs when lenders disagree (HL or LH), which carries no information content as lenders share the same precision: $p_{HL}(s) = \overline{p}_{HL}\phi(s) = \alpha(1-\alpha)\phi(s)$, and $\phi_1(s)\overline{p}_{LH} = \phi_1(s)\alpha(1-\alpha)$. Hence, Eq. (45) is determined by lending costs in competition HH:

$$\frac{d\Delta\pi\left(s;\eta\right)}{d\eta} = \frac{d\left[\phi_1\left(s\right)\int_0^s p_{HH}\left(t;\eta\right)dt - p_{HH}\left(s;\eta\right)\int_0^s \phi_1\left(t\right)dt\right]}{d\eta}.$$

Using $p_{HH}(s;\eta)$ given in Eq. (35), we have

$$\frac{d\Delta\pi\left(s;\eta\right)}{d\eta} = q_h^h \underbrace{\left(2\alpha-1\right)}_{+} \int_0^s \phi_0\left(t\right)\phi_0\left(s\right) \underbrace{\left[\frac{\phi_1\left(t\right)}{\phi_0\left(t\right)} - \frac{\phi_1\left(s\right)}{\phi_0\left(s\right)}\right]}_{-,MLRP} dt < 0.$$

The bracketed term $\frac{\phi_1(t)}{\phi_0(t)} - \frac{\phi_1(s)}{\phi_0(s)} = \frac{t}{1-t} - \frac{s}{1-s} < 0$ for $t < s$.

Step 2. We now show the first part of the Proposition holds. In the zero weak regime, $\pi^B(\eta) = 0$ is a constant in η. We aim to show that in the positive weak regime where $\pi^B(\eta) > 0$, Bank B's profit $\pi^B(\eta)$ is strictly increasing in η.

We intend to find a particular soft signal $s \geq \hat{s}(\eta)$ and show that Bank A's profit upon s is strictly increasing in η. Then Step 1 implies that Bank B' profit must be strictly increasing in η as well. Consider any η_1, η_2, where $\eta_1 < \eta_2$ and $\pi^B(\eta_1) > 0, \pi^B(\eta_2) > 0$ (positive weak.) From Proposition 1, the equilibrium threshold $\hat{s}(\eta) = s_A^{be}(\eta)$ in the positive weak regime. Then Lemma 7, which says $s_{be}^A\left(\eta\right)$ decreases in η, shows

$$\hat{s}\left(\eta_1\right) = s_{be}^A\left(\eta_1\right) > s_{be}^A\left(\eta_2\right) = \hat{s}\left(\eta_2\right). \tag{46}$$

Consider the equilibrium when $\eta = \eta_2$. Since the equilibrium is positive weak, Bank A breaks even upon soft signal $\hat{s}\left(\eta_2\right)$. In addition, Step 1 in the proof of Lemma 9 in Online Appendix B.2 shows that Bank A's profit conditional on the soft signal s, is strictly increasing in s. Hence,

$$\frac{\pi^A\left(r^A\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_2\right)}{\phi\left(\hat{s}\left(\eta_1\right)\right)} \underbrace{>}_{\text{profit} \uparrow \text{ in } s} \frac{\pi^A\left(r^A\left(\hat{s}\left(\eta_2\right)\right),\hat{s}\left(\eta_2\right);\eta_2\right)}{\phi\left(\hat{s}\left(\eta_2\right)\right)} \underbrace{=}_{\text{def } \hat{s}(\eta_2)} 0. \tag{47}$$

The density adjustment $\frac{1}{\phi(s)}$ is included because the inequality holds for profit conditional on s (Lemma 9.) Now consider the equilibrium when $\eta = \eta_1$. From the definition of equilibrium threshold $\hat{s}(\eta_1)$,

$$\pi^A\left(r^A\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_1\right) \underbrace{=}_{\text{def } \hat{s}(\eta_1)} 0. \tag{48}$$

We now focus on the particular soft signal realization $s = \hat{s}\left(\eta_1\right)$ that satisfies $\hat{s}(\eta_1) \geq \max\{\hat{s}(\eta_1), \hat{s}(\eta_2)\}$ (see (46)) so that Step 1 applies. From (47) and (48), we have:

$$\pi^A\left(r^A\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_2\right) > 0 = \pi^A\left(r^A\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_1\right).$$

From Step 1 which implies $\Delta\pi\left(\eta_2\right) < \Delta\pi\left(\eta_1\right)$, Bank B benefits more from the higher η than Bank A:

$$\phi_1\left(\hat{s}\left(\eta_1\right)\right)\left[\pi^B\left(\hat{s}\left(\eta_1\right);\eta_2\right) - \pi^B\left(\hat{s}\left(\eta_1\right);\eta_1\right)\right] > \pi^A\left(r\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_2\right) - \pi^A\left(r^A\left(\hat{s}\left(\eta_1\right)\right),\hat{s}\left(\eta_1\right);\eta_1\right) > 0.$$

Since Bank B makes a constant profit, the above inequality says $\pi^B(\eta_2) > \pi^B(\eta_1)$. This claim holds for any $\eta_1 < \eta_2$ in the positive weak regime.

Therefore, $d\pi^B(\eta)/d\eta > 0\,(=0)$ if $\pi^B(\eta) > 0\,(=0)$. Since $\frac{d\pi^B}{d\eta} > 0$ in the positive weak regime, there exists a threshold information span above which the equilibrium is positive weak.

Step 3. We show the second part of the proposition. From Lemma 6, in the positive weak regime,

$$\mathbb{E}(\pi^A;\eta) - \pi^B(\eta) = \int_{\hat{s}}^{1} \Delta\pi(s;\eta)\,ds - \int_0^x \phi_1(s)\pi^B(\eta)ds.$$

Take derivative with respect to η,

$$\frac{d\left[\mathbb{E}(\pi^A;\eta) - \pi^B(\eta)\right]}{d\eta} = \int_{\hat{s}(\eta)}^{1} \underbrace{\frac{d\Delta\pi(s;\eta)}{d\eta}}_{\text{Step 1:}<0} ds - \phi_1(s)\int_0^{x(\eta)=\hat{s}(\eta)} \underbrace{\frac{d\pi^B(\eta)}{d\eta}}_{\text{Step 2:}>0} ds - \underbrace{\left[\Delta\pi(\hat{s};\eta) + \phi_1(s)\pi^B(\eta)\right]}_{=\pi^A(\overline{r},\hat{s})=0,}.$$

We have shown $\frac{d\Delta\pi(s;\eta)}{d\eta} < 0$ for $s \geq \hat{s}$ in Step 1 and $\frac{d\pi^B(\eta)}{d\eta} > 0$ in Step 2, and the third bracketed term, which captures the effects on the integration limits, is zero. Therefore, $d\pi^B/d\eta > d\mathbb{E}\left[\tilde{\pi}^A\right]/d\eta$. ☐

References

Agarwal, Sumit, Shashwat Alok, Pulak Ghosh, and Sudip Gupta, 2020, Financial inclusion and alternate credit scoring for the millennials: role of big data and machine learning in fintech, *Business School, National University of Singapore Working Paper, SSRN* 3507827.

Babina, Tania, Greg Buchak, Filippo De Marco, Angus Foulis, Will Gornall, Francesco Mazzola, and Tong Yu, forthcoming, Customer data access and fintech entry: Early evidence from open banking, *Journal of Financial Economics*.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri, 2020, On the rise of fintechs: Credit scoring using digital footprints, *Review of Financial Studies* 33, 2845–2897.

Berg, Tobias, Andreas Fuster, and Manju Puri, 2022, Fintech lending, *Annual Review of Financial Economics* 14, 187–207.

Bertomeu, Jeremy, and Iván Marinovic, 2016, A theory of hard and soft information, *The Accounting Review* 91, 1–20.

Blickle, Kristian, Zhiguo He, Jing Huang, and Cecilia Parlatore, 2025, Information-based pricing in specialized lending, *Journal of Financial Economics* 172, 104–135.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders, 2023, Specialization in banking, *FRB of New York Staff Report No. 967*.

Broecker, Thorsten, 1990, Credit-worthiness tests and interbank competition, *Econometrica* pp. 429–452.

Corrao, Roberto, 2023, Mediation markets: The case of soft information, Discussion paper Working Paper.

Crawford, Gregory S, Nicola Pavanini, and Fabiano Schivardi, 2018, Asymmetric information and imperfect competition in lending markets, *American Economic Review* 108, 1659–1701.

Crawford, Vincent P, and Joel Sobel, 1982, Strategic information transmission, *Econometrica: Journal of the Econometric Society* pp. 1431–1451.

Ghosh, Pulak, Boris Vallee, and Yao Zeng, 2022, Fintech lending and cashless payments, in *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI-ESSEC*.

Goldstein, Itay, Chong Huang, and Liyan Yang, 2022, Open banking with depositor monitoring, *Working paper*.

Hardik, Nimbark, 2023, Digitalisation promotes adoption of soft information in sme credit evaluation: the case of indian banks, *Digital Finance* pp. 1–32.

Hauswald, Robert, and Robert Marquez, 2003, Information technology and financial services competition, *Review of Financial Studies* 16, 921–948.

He, Zhiguo, Jing Huang, and Jidong Zhou, 2023, Open banking: Credit market competition when borrowers own the data, *Journal of Financial Economics* 147, 449–474.

He, Zhiguo, Sheila Jiang, Douglas Xu, and Xiao Yin, 2025, Investing in lending technology: It spending in banking, *Management Science*.

Huang, Jing, 2023, Fintech expansion, *Available at SSRN 3957688*.

Huang, Yiping, Longmei Zhang, Zhenhua Li, Han Qiu, Tao Sun, and Xue Wang, 2020, Fintech credit risk assessment for smes: Evidence from china, .

Karapetyan, Artashes, and Bogdan Stacescu, 2014, Information sharing and information acquisition in credit markets, *Review of Finance* 18, 1583–1615.

Kremer, Michael, 1993, The o-ring theory of economic development, *The Quarterly Journal of Economics* 108, 551–575.

Liberti, Jose M., and Atif R. Mian, 2009, Estimating the effect of hierarchies on information use, *The Review of Financial Studies* 22, 4057–4090.

Liberti, José María, and Mitchell A Petersen, 2019, Information: Hard and soft, *Review of Corporate Finance Studies* 8, 1–41.

Marquez, Robert, 2002, Competition, adverse selection, and information dispersion in the banking industry, *Review of Financial Studies* 15, 901–926.

Milgrom, Paul, and Robert J Weber, 1982, The value of information in a sealed-bid auction, *Journal of Mathematical Economics* 10, 105–114.

Milgrom, Paul R, 1981, Good news and bad news: Representation theorems and applications, *The Bell Journal of Economics* pp. 380–391.

Paravisini, Daniel, and Antoinette Schoar, 2016, The incentive effect of scores: Randomized evidence from credit committees,, *NBER Working Paper, 19303*.

Stein, Jeremy C., 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *The Journal of Finance* 57, 1891–1921.

Vives, Xavier, 2019, Digital disruption in banking, *Annual Review of Financial Economics* 11, 243–272.