Information-Based Pricing in Specialized Lending *

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Abstract

We study specialized lending in a credit market competition model with private information. Two banks, equipped with similar data processing systems, possess general signals regarding the borrowers quality; the specialized bank, has access to an additional specialized signal. We study equilibria in which both lenders use general signals to screen loan applications. Conditional on making an offer, the specialized lender prices loans based on its specialized signal. This private-information-based pricing helps explain why loans made by specialized lenders have lower interest rates (lower winning bids) and better ex-post performance (fewer non-performing loans), which we support with robust empirical evidence.

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

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1 Introduction

Competition among informed financial intermediaries in the credit market is central to the efficiency of financial systems (see, e.g., Broecker, 1990; Riordan, 1993; Hauswald and Marquez, 2003), The efficiency of credit allocation is fundamentally shaped by the informational environment in which banks operate. Banks rely on various sources of information, ranging from borrower financial statements and proprietary data, to assess credit risk and make lending decisions.

Importantly, banks are heterogeneous in their informational capacity. Empirical evidence suggests that banks have specialized expertise in particular industries or borrower segments, leveraging their informational advantages to tailor lending practices ((Blickle, Parlatore, and Saunders, 2023)). This specialization reflects the multidimensional nature of information that banks possess, encompassing quantitative metrics such as balance sheet data and qualitative (soft) insights derived from relationship lending or industry-specific knowledge. In addition, these different types of information tend to cover different aspects of the borrower relevant to their creditworthiness. The prominent heterogeneity and multidimensionality of bank information raise important questions about how these factors affect credit market competition and the ensuing allocation and pricing of loans.

In this paper, we study how private-information-based pricing emerges in equilibrium under competition between asymmetrically informed banks. Borrower quality depends on two different fundamental states. While both non-specialized and specialized lenders observe private signals on one state, the specialized lender is "more" informed in the sense that it observes an additional private signal on the other state. Thus, we extend the classic credit market competition framework (a la Broecker (1990)) to explore the interplay between multidimensional information and equilibrium loan pricing. Specifically, our analysis focuses on how these informational asymmetries shape the equilibrium strategies of specialized and non-specialized lenders, thereby shedding light on the nuanced role of information in credit market outcomes. Beyond our theoretical analysis, we explore the relation between bank specialization and realized rates, for large, stress-tested U.S. banks and link it to our theoretical findings.

Taking as a starting point the finding in Blickle, Parlatore, and Saunders (2023) that banks specialize in certain industries, we motivate our mechanism of information-based pricing by a simple empirical exercise. Using regulatory loan-level data from the Y14-Q Schedule H database maintained by the Fed, for each year, we compute the difference between the average interest rate of loans granted by specialized banks in their industry of specialization and those of their loans in other industries. Figure 1 shows that specialized lenders consistently charge around 40 basis points less for loans in their specialized industry. This difference is on "winning bids" rather than "bids"—since our loan-level data is based on granted loans, not loan offers—which is an important distinction through the lens of our credit market equilibrium model. Equally important, Figure 1 shows that specialized lenders are less likely to encounter non-performing loans in their industry of specialization. The empirical regularity documented in Figure 1, which is robust to more stringent econometric specifications (Section 4.4), suggests that specialized lenders can identify better borrowers and "undercut" their non-specialized opponents in their specialized industries.

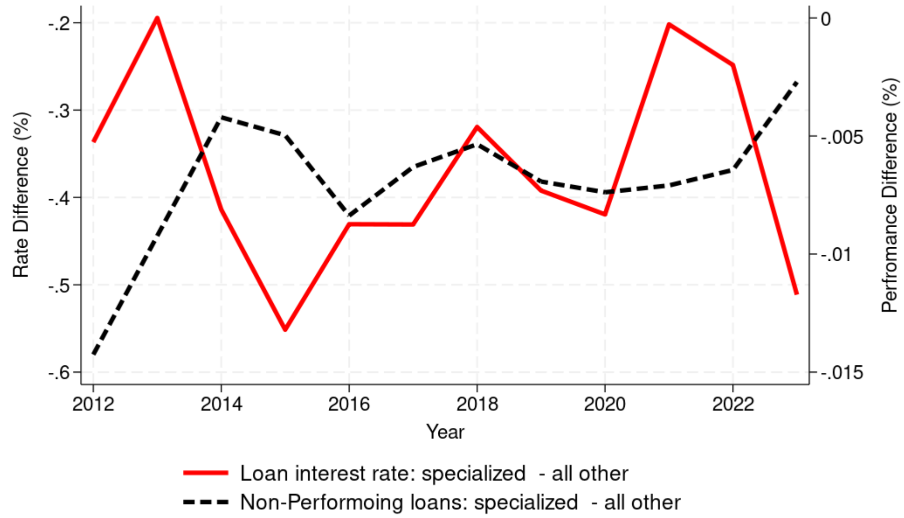

Figure 1: **Differences in interest rates and loan performance between specialized and non-specialized lenders.** We define specialized lenders as those with more than 4% over-investment in an industry, where over-investment is measured as deviations from a diversified portfolio $\frac{LoanAmount_{b,i,t}}{\sum_s LoanAmount_{b,i,t}} - \frac{LoanAmount_{i,t}}{\sum_i LoanAmount_{i,t}}$ for bank b in industry i at time t. The red solid line (left-hand side scale) plots the average difference between loan annual interest rates in the bank's specialized industry and those outside of its specialized industry. The dashed black line (right-hand side scale) plots the average annual differences in the fraction of non-performing loans when comparing loans in a bank's specialized industry against its other loans. The patterns are robust to various specifications of specialized lenders and volume-based weights; for details, see Appendix B. For a more in-depth discussion of measures of bank specialization, see Blickle, Parlatore, and Saunders (2023).

The existing information-based models, e.g., Broecker (1990) and Marquez (2002), however, fail to deliver the above empirical regularity. As Section 4 shows, a stark information rent effect dominates in these canonical settings, in which the loans in the book of a stronger lender (with a more precise signal) tend to charge higher interest rates, contrary to Figure 1.

In our model, both specialized and non-specialized banks have a "general" information signal on the loan quality, say from analyzing the borrower's financial statement. This is the canonical setting analyzed in Broecker (1990); we further assume that the specialized lender has access to an additional signal from "specialized" information about the borrower. While the general signal is binary and decisive in that each lender considers making an offer only upon receiving a positive general signal, the specialized signal—which differentiates our paper from existing models—is continuous and guides the fine-tuned interest rate offering of the specialized bank. When the specialized signal is sufficiently low, the specialized lender rejects the borrower, just as in practice.[1]

We focus on a multiplicative structure (similar to the O-ring theory) so that project success

[1]Besides providing analytical convenience, this loan-making rule matches the lending practices observed in practice. Essentially, in our model, the specialized bank acquires two signals, one being "principal" while the other being "supplementary;" the former determines whether to lend while the latter affects the detailed pricing terms. The principal signal can also represent the result of a credit screening test, while the supplementary signal serves the role of internal ratings (of borrowers who qualify for credit).

requires two distinct fundamental states "general" and "specialized" to be favorable;[2] and the two types of signals mentioned above–general and specialized–inform the lenders regarding these two states, respectively. Section 3 characterizes in closed form the competitive credit market equilibrium with specialized lending, where the specialized bank's interest rate schedule is *decreasing* in its specialized signal. In contrast, the non-specialized bank behaves just as in Broecker (1990) fully randomizing its interest rate offers. Therefore by incorporating both general and specialized signals, our model delivers the key result of private-information-based pricing.[3]

We derive a unique credit market equilibrium that can fall into two distinct categories depending on the competitiveness of the banking industry. In the first category of equilibria, the winner's curse pushes the non-specialized "weak" bank to earn zero profits. We therefore call it a zero-weak equilibrium, where the non-specialized bank randomly withdraws upon a positive general signal, consequently yielding more monopoly power to its specialized opponent. In the second category of equilibria, the non-specialized bank makes a positive profit in equilibrium (therefore always participates upon a positive general signal); we call it a positive-weak equilibrium.

Section 5 discusses the implications of the model. We focus on the "negative interest rate wedge,", i.e. the empirical regularity that loans from specialized lenders have lower rates. First, we highlight the difference between *bids* (i.e., offered interest rates) and *winning bids* (offered rates accepted by the borrower). This distinction is crucial when loan rejections are an important part of equilibrium strategies, as is typical in credit competition models. Although the standard winner's curse effect pushes the weaker lender to quote higher interest rates, in credit market competition models like He, Huang, and Zhou (2023) the weak lender also responds by rejecting loan applications. In equilibrium, the strong lender exerts its monopolistic power by randomly quoting the maximum interest rate (which might be accepted in equilibrium), resulting in a higher expected rate for loans granted by specialized lenders. We call this the *information rent* effect.

In contrast, by modeling specialized signals, we explicitly incorporate the specialized lender's "undercutting" to win creditworthy borrowers, favoring a lower expected rate for granted loans by specialized lenders. We call this the "private-information-based pricing" effect, which prevails especially in the positive-weak regime: the specialized bank has less monopoly power and hence makes more aggressive offers to get good borrowers, as explained above.[4]

[2]This setting is quite general, as the general and specialized fundamental states can potentially overlap; see He, Huang, and Parlatore (2024) apply this setting to study the role of information span in credit market competition. To the extreme, these two fundamental states coincide entirely, and our model becomes the standard setting where one single fundamental state dictates the overall quality of the project.

[3]Conceptually, this is similar to the common value auction setting in Milgrom and Weber (1982), where the informed buyer who privately observes a continuum of signal realizations bids monotonically based on its private information (see literature review for more details). In addition, one could extend the range of quoted interest rates by borrowers to include infinity and interpret $r = \infty$ as "rejection;" this way the lenders in the classic credit market competition model in Broecker (1990) also have private-information-based pricing. However, Figure 1 is constructed based on interest rates of granted loans, which excludes $r = \infty$; we stress this point in Section 4 where we discuss the distinction between "bids" and "winning bids."

[4]Consistent with information-based pricing, Butler (2008) finds local investment banks charge lower fees and issue municipal bonds at lower yields than non-local underwriters. On the other hand, Degryse and Ongena (2005) finds that local banks charge higher interest rates to small firms, consistent with local banks' strong monopolistic power over hard-to-evaluate captive borrowers.

As one of the main results of our paper, Section 4 shows that canonical credit competition models have a hard time generating the empirical regularity of a "negative interest rate wedge." We show that under empirically relevant parameters, the information rent effect dominates in canonical credit competition models a la Broecker (1990), yielding the counterfactual implications. Our mechanism of private-information-based pricing, which naturally helps deliver a "negative interest rate wedge," differs from those of Mahoney and Weyl (2017) and Crawford, Pavanini, and Schivardi (2018). In that literature, market power (of lenders) and adverse selection (of borrowers) are treated as two distinct market frictions, whereas our model features the winner's curse as the only underlying force for both market power and adverse selection.

We explore several extensions. First, we endogenize the information structure by considering two ex-ante symmetric banks competing in two industries. Lenders can invest in a general information technology (fixed cost, binary signal of borrower quality) and also acquire costly, firm-specific specialized information (continuous signal) to become specialized; each lender only needs to invest once in the general information technology for the two industries but has to acquire the specialized signal separately for each industry. We provide conditions for a "symmetric" specialization equilibrium, where each industry has one specialized and one non-specialized lender, as in our baseline model. Second, we show that our equilibrium characterization is robust to a generalized information structure that allows for correlated general and specialized signals.

The remainder of the paper is organized as follows. After a brief review of the literature, Section 2 presents the baseline model, whose equilibrium is characterized in Section 3. Section 4 studies interest rate wedge and Section 5 explores several model extensions. Section 6 concludes.

Literature Review

Lending market competition and common-value auctions. Our paper builds on Broecker (1990), which studies lending market competition with screening tests and symmetric lenders (i.e., with the same screening abilities). Relatedly, Hauswald and Marquez (2003) explores the competition between an inside bank that can conduct credit screenings and an outside bank without such access.[5] In these models, for analytical tractability, it is often assumed that private screening yields a binary signal and lenders participate only when receiving the positive signal realization. In contrast to these papers, we consider competition between asymmetrically informed lenders with multiple information sources.

Theoretically, credit market competition models are an application of common-value auctions. Notably, the auction literature typically allows for general signal distributions (other than the binary

[5] Asymmetric credit market competition can also naturally arise from the bank-customer relationship, as a bank knows its existing customers better than a new competitor. This idea was explored by a two-period model in Sharpe (1990) where asymmetric competition arises in the second period (with the corrected analysis of a mixed-strategy equilibrium offered by Von Thadden (2004)). A similar analysis is present in Rajan (1992). Recently, under the open banking policy proposal, He, Huang, and Zhou (2023) consider competition between asymmetric lenders with different screening abilities under open banking when borrowers control access to data, and Goldstein, Huang, and Yang (2022) highlight the endogenous response from banks' liability side once the incumbent bank's borrower data become "open to a challenger bank," where maturity transformation of using short-term funding to support long-term loans plays an important role.

signal in the aforementioned papers).[6] For instance, Riordan (1993) extends the N-symmetric-lender model in Broecker (1990) to a setting with continuous private signals. In terms of modeling, our framework can be viewed as a combination of Broecker (1990) (symmetric bidders with general signals) and Milgrom and Weber (1982) (asymmetric bidders, one with a specialized signal). In our model, lenders are each privately informed with potentially different general signals. This breaks the Blackwell ordering of the information of two lenders in Milgrom and Weber (1982), resulting in a considerably more challenging problem.[7]

Specialization in lending. There is a growing literature documenting specialization in bank lending; for an early paper, see Acharya, Hasan, and Saunders (2006). More recently, Paravisini, Rappoport, and Schnabl (2023) show that Peruvian banks specialize their lending across export markets benefiting borrowers who obtain credit from their specialized banks. Based on data for US stress-tested banks, Blickle, Parlatore, and Saunders (2023) show that banks specialize their portfolios in different industries in a way consistent with them having greater informational advantages in industries in which they specialize more. This informational advantage manifests itself as better loan performance at the cost of some aggregate profitability in the industry in which the bank specializes relative to all other industries in the portfolio. Besides providing a framework that can rationalize observed specialization patterns, allowing us to better understand the economic mechanisms behind them and their implications,[8] our empirical results show that specialized banks have fewer non-performing loans issued at lower rates in their portfolios than non-specialized banks in the same industry, and that this result is not due to competition among specialized banks.

The connection to imperfect competition and adverse selection in the IO literature. The empirical pattern and our theoretical analyses on the negative interest rate wedge between asymmetrically informed lenders are connected to the industrial organization (IO) literature on imperfect competition and adverse selection (Mahoney and Weyl, 2017; Crawford, Pavanini, and Schivardi, 2018; Yannelis and Zhang, 2023). As we explain in detail in Section 4, different from the IO literature which takes market power (of lenders) and adverse selection (of borrowers) as two independent market frictions, our theory is based on "asymmetric information'," which is a more primitive assumption, with winner's curse faced by asymmetrically informed lenders as the only underlying economic force. Strictly speaking, in our model, there is no market power enjoyed by the specialized lender as money from any funding source is perfectly fungible; and, there is no adverse selection from borrowers either, as both types of borrowers will take loans at any interest rate.[9]

[6] The early papers on this topic include Milgrom and Weber (1982) and Engelbrecht-Wiggans, Milgrom, and Weber (1983), and later papers such as Hausch (1987); Kagel and Levin (1999) explore information structures where each bidder has some private information, which is the information structure adopted in Broecker (1990).

[7] More precisely, one bidder knows strictly more than the other bidder. In this setting, one can show that the under-informed bidder always makes zero profit; see also Engelbrecht-Wiggans, Milgrom, and Weber (1983).

[8] Our paper also connects to the growing literature on fintech disruption; see Berg, Fuster, and Puri (2021); Vives (2019), for instance, for a review of fintech companies competing with traditional banks in originating loans.

[9] Our paper is also related to the literature on the nature of information in bank lending. Berger and Udell (2006) provides a comprehensive framework of the two fundamental types of bank lending technology, i.e., relationship lending and transactions lending, in the SME lending market; these two types of lending are related to the role played by information as highlighted by Stein (2002); Paravisini and Schoar (2016). Recently, based on Harte Hanks

2 Model

In this section, we present the model and define the equilibrium accordingly.

2.1 General Setting

We consider a credit market competition model with two dates, one good, and risk-neutral agents (two lenders and one borrower). There are two lenders (banks) indexed by $j \in \{A, B\}$, where Bank A (B) is the specialized (non-specialized) lender.

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 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

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

where $\overline{r} > 0$ is exogenously given, i.e., only a good project has a positive NPV. We will later refer to $\overline{r}$ as the interest rate cap or the return of a good project. The project's quality θ is unobservable to lenders, and the prior probability of a good project is $q \equiv \mathbb{P}(\theta = 1)$.

Credit market competition. At date $t = 0$, each bank j can choose to make a take-it-or-leave-it interest rate offer $r^j \leq \overline{r}$ of a fixed loan amount of one to the borrower or to make no offer (i.e., exit the lending market), which we normalize as $r^j = \infty$. The borrower accepts the offer with the lowest rate if it receiving multiple offers.[10]

Information technology. Banks have access to information about the borrower's project quality before choosing whether to make an offer. We assume that both lenders have access to "general" data (say financial and operating data), which they can process to produce a *general-information*-based private signal g^j. We call these information "general" signals. We assume that these general signals are binary, i.e., $g^j \in \{H, L\}$, with a realization H (L) being a positive (negative) signal; and that, conditional on the (relevant) state, general signals are independent across lenders. Besides following the traditional structure presented in Broecker (1990), this modeling of general signals also captures the coarseness with which some general information is used in practice. For example, as a leading example of "general information," credit scores are binned in five ranges even though scores are computed at a much granular level and go from 300 to 850.

data, He, Jiang, Xu, and Yin (2023) show a significant rise in IT investment within the U.S. banking sector over the past decade, particularly among large banks, and their causal link between communication IT spending and the enhancement of banks' capacity in generating and transmitting soft information motivates our modeling of the specialized signal as the outcome of interactions with borrowers.

[10] We implicitly assume that borrowers obtain some (however small) private benefit, so it is strictly optimal to take the project even for the type $\theta = 0$. One important implication is that it is irrelevant whether borrowers privately know θ or not, as both types of borrowers always pool in equilibrium.

Additionally, we endow Bank A with a signal s, which captures the bank being "specialized." As the major departure from the existing literature, this additional signal is as a *specialized-information*-based private signal, which is collected, for example, after due diligence or face-to-face interactions with the borrower after on-site visits. We assume that the specialized signal s is continuous, and its distribution is characterized by the Cumulative Distribution Function (CDF) $\Phi(s)$ and probability density function (pdf) $\phi(s)$. Besides providing mathematical convenience, the continuous distribution captures "specialized" signals resulting from research tailored to the particular borrower and, therefore, allows for a more granular assessment of the borrower's quality.

The information structure is incomplete unless we specify the correlations between the fundamental states and the two types of signals, to which we turn in the next section.

2.2 The Setting with a Multiplicative Structure

General and specialized fundamental states. Our main analysis focuses on the specific setting with a multiplicative structure for the state θ, so that

$$\theta \equiv \theta_g \theta_s \equiv \begin{cases} 1, & \text{when } \theta_g = \theta_s = 1, \\ 0, & \text{when either } \theta_g = 0 \text{ or } \theta_s = 0. \end{cases} \tag{2}$$

Here, $\theta_g \in \{0,1\}$ captures the "*g*eneral" state and $\theta_s \in \{0,1\}$ captures the "*s*pecialized" state; they jointly determine the project's success θ, in that the project fails when *either* state fails.

We further assume that general and specialized states are independent, so that the prior probability of the state being "1" is simply $q = q_g q_s$ with $q_g \equiv \mathbb{P}(\theta_g = 1)$ and $q_s \equiv \mathbb{P}(\theta_s = 1)$. This independence, together with the independence of the noise across signals, implies complete independence between the generalized and specialized signals (for Bank A).

The distribution of the signals conditional on the state reflects the information technology. We assume that conditional on the state, the signal realizations are independent across borrowers. It is straightforward to allow for correlated signals conditional on the state (see He, Huang, and Parlatore (2024)). For general information signals, which are assumed to be binary, we assume

$$\mathbb{P}\left(g^j = H \,|\theta_g = 1\right) = \alpha_u \in [0,1]\,,\ \mathbb{P}\left(g^j = L \,|\theta_g = 0\right) = \alpha_d \in [0,1]\,, \quad \text{for} \quad j \in \{A, B\}\,. \tag{3}$$

Here, the information technology is not indexed by lender j—that is to say, lenders have the same technology to process general information that comes from "general" sources like financial statements, an assumption that we relax in Section 5.2.

In (3), $1-\alpha_u$ and $1-\alpha_d$ capture the probabilities of Type I and Type II errors, respectively. The bad-news signal structure in He, Huang, and Zhou (2023) corresponds to $\alpha_u = 1$ and a symmetric signal structure has $\alpha_u = \alpha_d = \alpha \in (0.5, 1]$ as in Hauswald and Marquez (2003) and He, Jiang, and Xu (2024). Our main numerical illustration focuses on the latter case, although our solution is robust to any $\{\alpha_u, \alpha_d\}$ structure.

For the continuous specialized signal, without loss of generality, we directly work with the posterior of the specialized state being good $\theta_s = 1$ given its signal realization, i.e.,

$$s = \Pr[\theta_s = 1 | \mathcal{F}_s] \in [0, 1], \tag{4}$$

where $\mathcal{F}_s$ is Bank A's information set regarding specialized signal. Note $\int_0^1 s\phi(s)\,ds \equiv q_s$ in order to satisfy prior consistency, where $\phi(s)$ denotes the pdf of s.

General signals being decisive. The specialized Bank A has both general and specialized signals $\{g^A, s\}$ while Bank B only has a general signal g^B. Throughout we assume that the general signal is "decisive" for lending: Bank j bids only if it receives $g^j = H$. Therefore the general signal serves as "pre-screening" for Bank A, i.e., it rejects the borrower upon $g^A = L$ while upon $g^A = H$ it makes a pricing decision based on its specialized signal s. We impose the following parameter restrictions to ensure the pre-screening general signal is decisive.

Assumption 1. ***(Decisive general signals)***
i) Bank A rejects the borrower upon an L general signal, regardless of any specialized signal s:

$$q_g (1 - \alpha_u) \overline{r} < (1 - q_g) \alpha_d. \tag{5}$$

ii) Bank B is willing to participate (i.e., $r^B < \infty$) if its general signal $g^B = H$:

$$q_g \alpha_u q_s \overline{r} > q_g \alpha_u (1 - q_s) + (1 - q_g)(1 - \alpha_d); \tag{6}$$

Under Condition (5), the loan is negative NPV to Bank A upon $g^A = L$, even for the most favorable specialized signal $s = 1$. This condition implies that Bank B, which only has the general signal and is uncertain about the realization of the specialized fundamental, also rejects the loan upon receiving $g^B = L$. Condition (6) states that upon $g^B = H$, Bank B is willing to lend at $\overline{r}$ if it is the monopolist lender.

2.3 Discussions on Model Assumptions

There are several model assumptions that are worth discussing further.

Multi-dimensional information structure and its general applications. Our setting with multiple states admits many other interpretations besides general and specialized states. Consider the following multi-dimensional multiplicative setting,

$$\theta = \overbrace{\prod_{n=1}^{\hat{N}} \theta_n}^{\theta_g} \cdot \overbrace{\prod_{n=\hat{N}+1}^{N} \theta_n}^{\theta_s}, \tag{7}$$

with independent binomial states (or characteristics) $\theta_n \in \{0, 1\}$ where $n \in \{1, 2, ..., N\}$; as shown, our model sets $\theta_g \equiv \prod_{n=1}^{\hat{N}} \theta_n$ and $\theta_s \equiv \prod_{n=\hat{N}+1}^{N} \theta_n$. One can always "relabel" to suit the context of a specific application. In a companion paper, He, Huang, and Parlatore (2024) interpret $\prod_{n=1}^{\hat{N}} \theta_n$ and $\prod_{n=\hat{N}+1}^{N} \theta_n$ as the "hard" and "soft" fundamental states, respectively.

Independence between general and specialized states. The assumption that the general state θ_g and the specialized state θ_s are independent is for ease of exposition only. Section 5.2 shows that independence can be relaxed while maintaining tractability. In a companion paper that explores the "span of information" He, Huang, and Parlatore (2024) allows for the two "hard" and "soft" fundamental states to be potentially correlated, which implies the general signals and the specialized signal for Bank A are correlated. For more details, see Section 5.2.

Principal and supplementary signals and comparison to the literature. The equilibrium loan-making rule of the specialized bank is practically relevant. Essentially, the specialized bank has two signals—the general one is "principal" that determines whether to lend, and the other specialized one is "supplementary" which helps its loan pricing.[11] This is in sharp contrast to the existing literature mentioned in the introduction where lenders make loan offers randomly only conditional on the most favorable realization of their (binary) signals. As shown in Section 4, our setting—by decoupling the lender's *ex-post* loan assessment from its *ex-ante* technology strength—helps deliver the empirical regularity of lower granted loan rates by specialized banks.

Endogenous information structure. In our main analysis, we take the lenders' information technologies—specifically, Bank A being the specialized lender—as given. Section 5.1 endogenizes this "asymmetric" information technology in a "symmetric" setting with two firms, a and b, where Bank A (B) endogenously becomes specialized by acquiring both "general" and "specialized" signals of the firm a (b), while non-specialized Bank B (A) only acquires the "general" signal of the firm a (b). There, the key difference between these two signals is that a lender j only needs to invest once—say installing IT equipment and software—to get two general signals, one for each firm, while specialized signal needs to be collected individually for each firm.

Non-zero loan recovery when default. To simplify the exposition, we follow the literature (Broecker, 1990; Marquez, 2002; He, Huang, and Zhou, 2023) to assume a zero recovery for defaulted loans. That is, we set $y = 0$ when $\theta = 0$ in Eq. (1). It is straightforward to allow for a non-zero loan recovery $y = \delta \in (0, 1)$ when $\theta = 0$, and we derive the resulting equilibrium in closed-form in Appendix A.3. Clearly, a non-zero recovery matters when we calibrate information technology parameters to match empirical moments, an exercise we undertake later in Section 4.2. There, we also derive the version of canonical models with non-zero recovery (see details in Appendix A.3) for the robustness of model implications on the predicted sign of interest rate wedge.

[11] Alternatively, the principal signal represents the result of a credit screening test, while the supplementary signal serves the role of internal ratings (of borrowers who are qualified for credit). This ranking portrays the key role played by hard information for large banks when dealing with new borrowers. Indeed, as documented on page 1677 of Crawford, Pavanini, and Schivardi (2018), Italian large banks list the factors they consider in assessing any new loan applicant's creditworthiness, with the following order of importance: i) hard information from the central bank (financial statement data); ii) hard information from Credit Register; iii) statistical-quantitative methods; iv) qualitative information (i.e., bank-specific soft information codifiable as data); v) availability of guarantees; and vi) first-hand information (i.e., branch-specific soft information).

2.4 Credit Market Equilibrium Definition

We now formally define the credit market equilibrium with specialized lending. Before doing so, we define the banks' strategies and their associated profits.

Bank strategies. In equilibrium, each lender makes a potential offer only upon receiving a positive general signal H—recall Assumption 1 guarantees that the general signals are "decisive" for both lenders in making the loan offer or not. Conditional on making offers, we define the space of interest rate offers by $\mathcal{R} \equiv [0, \bar{r}] \cup \{\infty\}$. Here, $\bar{r}$ is the exogenous interest rate cap (project return) imposed in Section 2.1 and ∞ captures the strategy of not making an offer. The endogenous support of the equilibrium interest rates offered will be a sub-interval of $[0, \bar{r}]$; so with a slight abuse of terminology we refer to that sub-interval as the "support" of the interest rate distribution even though loan rejection ($r = \infty$) could also occur along the equilibrium path.

We denote Bank A's pure strategy by $r^A(s) : [0,1] \to \mathcal{R}$, which induces a distribution of its offers denoted by $F^A(r) \equiv \Pr\left(r^A \leq r\right)$ according to the underlying distribution of the specialized signal. We take as given that Bank A uses pure strategy, though later we formally prove this result in Proposition 1. On the other hand, Bank B randomizes conditional on $g^B = H$, in which case we use $F^B(r) \equiv \Pr\left(r^B \leq r\right)$ to denote the cumulative distribution of its interest rate offers. Because the domain of offers includes rejection $r = \infty$, it is possible that $F^j(\bar{r}) = \mathbb{P}\left(r^j < \infty | g^j = H\right) \leq 1$ for $j \in \{A, B\}$.

The borrower chooses the lowest interest rate offered. For example, conditional on $g^A = g^B = H$, if Bank B quotes r^B, then its winning probability $1 - F^A(r^B)$ equals the probability that Bank A with s offers a rate higher than r^B—note, this includes the event of Bank A with $g^A = H$ rejecting the borrower ($r^A(s) = \infty$), presumably due to an unfavorable specialized signal. Upon ties $r^A = r^B < \infty$, borrowers randomly choose the lender with probability one-half, although the details of the tie-breaking rule do not matter (ties occur as zero-measure events in equilibrium). When $r^A = r^B = \infty$, no bank wins the competition as both reject the borrower.

Definition 1. (Credit market equilibrium) A competitive equilibrium in the credit market (with decisive general signals) consists of the following lending strategies and borrower choice:

1. A lender j rejects the borrower or $r^j = \infty$ upon $g^j = L$ for $j \in \{A, B\}$; upon $g^j = H$,
   i) Bank A offers $r^A(s) : [0,1] \to \mathcal{R} \equiv [0, \bar{r}] \cup \{\infty\}$ to maximize its expected lending profits given $g^A = H$ 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 lending profits given $g^B = H$, which induces a distribution function $F^B(r) : \mathcal{R} \to [0,1]$;
2. Whenever receiving at least one offer, the borrower chooses the lowest offer as long as $\min\{r^A, r^B\} < \infty$.

The following lemma shows that the resulting equilibrium strategies in our setting are still well-behaved as established in the literature (Engelbrecht-Wiggans, Milgrom, and Weber (1983);

Broecker (1990)). The key steps of the proof are standard, though we make certain adjustments due to the presence of both discrete and continuous signals.

Lemma 1. ***(Equilibrium Structure)*** *In any equilibrium, there exists an endogenous lower bound of interest rate $\underline{r} > 0$, so that the two distributions $F^j(\cdot)$, $j \in \{A, B\}$ share a common support $[\underline{r}, \overline{r}]$ (besides ∞ as rejection). Over $[\underline{r}, \overline{r})$ both distributions are smooth, i.e. no gap and atomless, so that they admit well-defined density functions. At most one lender can have a mass point at $\overline{r}$.*

Bank profits and optimal strategies. Denote by $g^A g^B \in \{HH, HL, LH, LL\}$ the event of two general signal realizations, where HL represents Bank A's (B's) general signal being H (L). Denote by $p_{g^A g^B}$ the joint probability of any collection of realizations of general signals; e.g., $p_{HH} \equiv \mathbb{P}\left(g^A = H, g^B = H\right) = q_g \alpha_u^2 + (1 - q_g)(1 - \alpha_d)^2$. Similarly, denote by $\mu_{g^A g^B} \equiv \mathbb{P}\left(\theta_g = 1 \middle| g^A, g^B\right)$ the posterior probability of the general state being one conditional on $g^A g^B$; for instance,

$$\mu_{HH} = \frac{q_g \alpha_u^2}{q_g \alpha_u^2 + (1 - q_g)(1 - \alpha_d)^2}.$$

And, since $\{\theta_g, \theta_s\}$ are independent, the posterior of project success given $\{HH, s\}$ is

$$\mathbb{P}\left(\theta = 1 \middle| g^A = H, g^B = H, s\right) = \mu_{HH} \cdot s. \tag{8}$$

For Bank A who receives $g^A = H$ and s, its profit $\pi^A(r|s)$ by quoting $r \in [\underline{r}, \overline{r}]$ equals

$$\pi^A(r|s) \equiv \underbrace{p_{HH}}_{g^A = g^B = H} \underbrace{\left[1 - F^B(r)\right]}_{A \text{ wins}} \left[\mu_{HH} s (1 + r) - 1\right] + \underbrace{p_{HL}}_{g^A = H, g^B = L} \left[\mu_{HL} s (1 + r) - 1\right]. \tag{9}$$

Bank A can also choose to exit by quoting $r = \infty$, in which case $\pi^A(\infty|s) = 0$. We then denote Bank A's optimal interest rate offer by

$$r^A(s) \equiv \arg\max_{r \in \mathcal{R}} \pi^A(r|s).$$

To understand Eq. (9), recall that Bank A cannot observe g^B when making an offer. With probability p_{HH}, both banks get favorable general signals and Bank A quoting r wins with probability $1 - F^B(r)$, whereas with probability p_{HL} it faces no competition as Bank B with $g^B = L$ withdraws itself. Standard winner's curse logic implies that whether Bank B participates in the loan market affects Bank A's perceived borrower quality (regarding the general fundamental state) captured by μ_{HH} or μ_{HL}. Importantly, since Bank B randomizes its strategy upon $g^B = H$, from the perspective of Bank A winning the price competition against Bank B is not informative about borrower quality.

This last observation is in sharp contrast with the problem of the non-specialized Bank B, who understands that the outcome of competition against its specialized opponent is informative about θ_s. More specifically, besides the possibility of the competitor's unfavorable general information as mentioned above, the non-specialized lender B knows that $r^A(s) > r^B$ upon winning the competition. Because the equilibrium $r^A(s)$ is decreasing, an important equilibrium property that we will verify later, upon winning Bank B infers an unfavorable specialized signal. Taking these inferences into account, Bank B's lending profit when quoting r is

$$\pi^B(r) \equiv \underbrace{p_{HH}}_{g^A=g^B=H} \underbrace{\left[1 - F^A(r)\right]}_{B \text{ wins}} \mathbb{E}\left[\mu_{HH}\theta_s(1+r) - 1 \middle| r \le r^A(s)\right] + \underbrace{p_{LH}}_{g^A=L, g^B=H} \left[\mu_{LH} q_s (1+r) - 1\right]. \tag{10}$$

Bank B's optimal strategy $F^B(\cdot)$ maximizes its expected payoff

$$\max_{F^B(\cdot)} \int_{\mathcal{R}} \pi^B(r)\, dF^B(r). \tag{11}$$

As it is standard in equilibria in mixed strategies, the profit-maximizing Bank B is indifferent between any r on its support.

3 Credit Market Equilibrium Characterization

To characterize the credit market equilibrium, in Section 3.1 we first take the equilibrium non-specialized Bank B's profit π^B as given and solve for the other equilibrium objects. We then solve for π^B in Section 3.2, and Section 3.3 completes the construction of the credit market equilibrium.

3.1 Solving for the Pricing Strategies of the Lenders

Solving for $r^A(s)$. We start by solving for Bank A's equilibrium strategy $r^A(s)$. Bank B who plays mixed strategies must make a constant profit $\pi^B \ge 0$ from any interest rate along the equilibrium support. Our goal is to characterize both lenders' strategies by taking π^B as given.

Suppose that $r^A(s)$ is decreasing, which we shall verify later. Then conditional on $g^A = H$, when Bank B quotes $r = r^A(s)$, it wins the borrower only when A's specialized signal is below s. Bank B, therefore, updates its beliefs about the borrower's quality accordingly—its posterior for the specialized state is $\int_0^s t\phi(t)\, dt$. On the other hand, conditional on $g^A = L$, Bank B wins the borrower for sure. Plugging $r^B = r^A(s)$ in Bank B's lending profits in Eq. (10), we have the following indifference condition:

$$\pi^B = \underbrace{\left[p_{HH}\mu_{HH}\int_0^s t\phi(t)\, dt + p_{LH}\mu_{LH} q_s\right]}_{B\text{'s expected loan quality (lending benefit)}} \left(1 + r^A(s)\right) - \underbrace{\left(p_{HH}\Phi(s) + p_{LH}\right)}_{B\text{'s expected loan size (lending cost)}}. \tag{12}$$

Eq. (12) holds for any $r^A(s) \in [\underline{r}, \overline{r})$, which implies that

$$r^A(s) = \frac{\pi^B + p_{HH}\Phi(s) + p_{LH}}{p_{HH}\mu_{HH}\int_0^s t\phi(t)\, dt + p_{LH}\mu_{LH} q_s} - 1. \quad \text{when} \quad s \in [\hat{s}, 1]. \tag{13}$$

where $\hat{s}$ is the highest specialized signal realization so that Bank A quotes $\overline{r}$:

$$\hat{s} \equiv \sup \left\{ s | \, r^A(s) = \overline{r} \right\}. \tag{14}$$

For worse signal realizations $s < \hat{s}$, Bank A keeps quoting $\overline{r}$ until a threshold $x \leq \hat{s}$ such that $\pi^A(\overline{r}| \, x) = 0$ and rejects borrowers upon $s < x$; i.e., $r^A(s) = \overline{r}$ for $s \in [x, \hat{s})$, and $r^A(s) = \infty$ for $s \in [0, x)$. Note that $x = \hat{s}$ can occur in equilibrium (which, as we will show, occurs when $\pi^B > 0$).

Because Bank A with the highest specialized signal $s = 1$ quotes $\underline{r}$, we have:

$$\underline{r} = r^A(1) = \frac{\pi^B + p_{HH} + p_{LH}}{(p_{HH}\mu_{HH} + p_{LH}\mu_{LH})q_s} - 1 \Leftrightarrow \pi^B = (1 + \underline{r}) \cdot (p_{HH}\mu_{HH} + p_{LH}\mu_{LH})q_s - (p_{HH} + p_{LH}). \tag{15}$$

Intuitively, by quoting $\underline{r}$ Bank B guarantees winning, so its profit equals $1 + \underline{r}$ multiplied by the probability of good borrower $(p_{HH}\mu_{HH} + p_{LH}\mu_{LH})q_s$ less the lending probability $p_{HH} + p_{LH}$.

Proposition 1 below shows that Bank A's strategy $r^A(s)$ is always decreasing in equilibrium (no ironing needed). Define its inverse function (correspondence) of $r^A(s)$ to be

$$s^A(r) \equiv \begin{cases} r^{A(-1)}(r), & \text{when } r \in [\underline{r}, \overline{r}), \\ [x, \hat{s}), & \text{when } r = \overline{r}, \\ [0, x), & \text{when } r = \infty. \end{cases} \tag{16}$$

The two relevant cutoffs for Bank A's strategy can be written as $\hat{s} = \sup s^A(\overline{r})$, i.e., the highest signal that Bank A quotes $\overline{r}$, and $x = \sup s^A(\infty)$, i.e., the highest signal under which Bank A rejects the borrower.

Solving for $F^B(\cdot)$. Recall Bank B is indifferent among all rates on the support; we pin down B's equilibrium strategy so that $r^A(\cdot)$ in Eq. (13) is A's optimal strategy. The first-order-condition (FOC) that maximizes Bank A's objective in Eq. (9) is

$$p_{HH}\left(-F^{B\prime}(r)\right)[\mu_{HH}s(1+r) - 1] + \left\{p_{HH}\left[1 - F^B(r)\right]\mu_{HH}s + p_{HL}\mu_{HL}s\right\} = 0. \tag{17}$$

Denote by $Q^A(r; s)$ and $Q^B(r)$ the total effective borrowers (who can repay) of Bank A and B when offering interest rate r, respectively:

$$Q^A(r; s) = p_{HH}\mu_{HH}s\left[1 - F^B(r)\right] + p_{HL}\mu_{HL}s,$$
$$Q^B(r) = p_{HH}\mu_{HH}\int_0^{s^A(r)} t\phi(t)\,dt + p_{LH}\mu_{LH}q_s.$$

Q^A and Q^B differ in that Bank A observes s while B only knows that it gets borrower types with $s < s^A(r)$ (if $g^A = H$) or q_s (if $g^A = L$); this is why $Q^A(r; s)$ depends on the specialized signal s.

As Bank A marginally increases the interest rate r, it gains $Q^A(r; s)dr$ from existing borrowers who repay, but its customer quality is also changed by $Q^{A\prime}(r; s)dr$ where $Q^{A\prime}(r; s) \equiv \frac{dQ^A(r;s)}{dr}$. As explained in footnote 12, Bank A's FOC (17) can be written as

$$\underbrace{Q^{A\prime}(r;s)\cdot\left(1+r-\frac{1}{\mu_{HH}s}\right)}_{\text{MB on marginal borrower type}}=\underbrace{-Q^{A}(r;s)}_{\text{MC on existing borrower types}},\tag{18}$$

where the marginal good borrower repays $1+r$ and the associated lending cost $\frac{1}{\mu_{HH}s}$ includes lending to lemons due to imperfect screening. Similarly, for Bank B, any interest rate r on support balances the change in its customers against the higher payoff from existing borrowers, and the FOC that maximizes Bank B's profits in Eq. (12) can be written as[12]

$$\underbrace{Q^{B\prime}(r)\cdot\left(1+r-\frac{1}{\mu_{HH}s^{A}(r)}\right)}_{\text{MB on marginal borrower type}}=\underbrace{-Q^{B}(r)}_{\text{MC on existing borrower types}}.\tag{19}$$

Evaluating (18) at the equilibrium borrower type $s=s^A(r)$ and combining it with (19), we have the following equation:

$$\frac{Q^{A\prime}\left(r;s^A(r)\right)}{Q^A\left(r;s^A(r)\right)}=\frac{Q^{B\prime}(r)}{Q^B(r)}\Leftrightarrow\frac{d}{dr}\left[\frac{Q^A(r;s)}{Q^B(r)}\right]\Bigg|_{s=s^A(r)}=0.\tag{20}$$

Intuitively, at any interest rate r, both lenders are competing for the same marginal borrowers. As each lender balances this marginal borrower's payoff with the payoff gain from existing customers, in equilibrium, their existing customers should change proportionally.

Factoring out s in $Q^A(r;s)$, (20) gives the following key ordinary differential equation (ODE):

$$\frac{d}{dr}\left\{\frac{p_{HH}\mu_{HH}\left[1-F^B(r)\right]+p_{HL}\mu_{HL}}{p_{HH}\mu_{HH}\int_0^{s^A(r)}t\phi(t)\,dt+p_{LH}\mu_{LH}q_s}\right\}=0.\tag{21}$$

We further invoke two boundary conditions, $F^B(\underline{r})=0$ and $\underline{r}(\pi^B)$ in (15), to solve for $F^B(\cdot)$. Focusing on the interior of the strategy space, we have:

$$1-F^B(r)=\frac{\int_0^{s^A(r)}t\phi(t)\,dt}{q_s},\ \text{for } r\in(\underline{r}.\overline{r})\tag{22}$$

Bank B's strategy on the upper boundary depends on whether it is profitable in equilibrium: it either places a mass of $1-F^B(\overline{r}^-)=\frac{1}{q_s}\int_0^{\hat{s}}t\phi(t)\,dt>0$ on $\overline{r}$ if $\pi^B>0$, or withdraws by quoting $r=\infty$ if $\pi^B=0$.[13]

[12] For Bank A, from (9) we have $\pi^A(r\,|s)=Q^A(r;s)\cdot(1+r)-(p_{HH}(1-F^B(r))+p_{HL})$. Taking derivative with respect to r and noticing $\frac{Q^{A\prime}(r)}{\mu_{HH}s}=-p_{HH}F^{B\prime}(r)$, we arrive at (18). Similarly, for Bank B from (12) we have $\pi^B(r)=Q^B(r)\cdot(1+r)-(p_{HH}\Phi(s^A(r))+p_{LH})$; noticing $\frac{Q^{B\prime}(r)}{\mu_{HH}s}=p_{HH}\phi(s)s^{A\prime}(r)$ allows us to derive (19). This result is surprising, as Q^j with $j\in\{A,B\}$ only captures lending revenues but not loan cost. However, the marginal cost is related to $Q^{j\prime}$ for both banks in the same way, because they compete for the same marginal borrower.

[13] Although the information technology parameters on the general signals do not enter $F^B(\cdot)$ in (22) directly, they

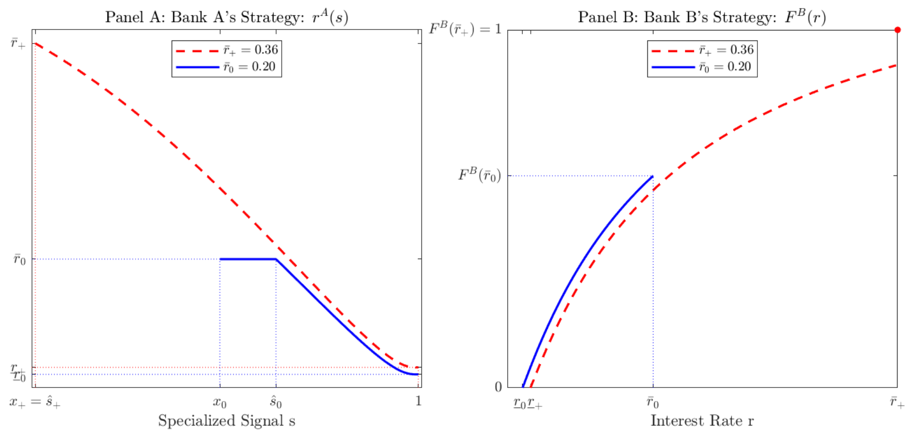

Figure 2: **Equilibrium strategies $r^A(s)$ for Bank A (left) and $F^B(r)$ for Bank B (right).** In both panels, strategies under $\bar{r}_+$ (i.e., positive-weak equilibrium) are depicted in red dashed lines while strategies with $\bar{r}_0$ (i.e., zero-weak equilibrium) are depicted in blue solid lines. In the zero-weak equilibrium, Bank A (but not Bank B) has a point mass at $\bar{r}_0$ while in the positive-weak equilibrium, Bank B (but not Bank A) has a point mass at $\bar{r}_+$. Parameters: $q_g = 0.75$, $q_s = 0.95$, $\alpha_u = \alpha_d = \alpha = 0.85$, and $\tau = 1$, where τ captures the signal-to-noise ratio of Bank A's specialized information technology as $s = \mathbb{E}[\theta_s|\theta_s + \epsilon]$ and $\epsilon \sim \mathcal{N}(0, 1/\tau)$.

Illustration of lenders' pricing strategies. Figure 2 illustrates the equilibrium strategies for both lenders for two cases, $\pi^B > 0$ and $\pi^B = 0$ indicated by the subscripts "+" and "0," respectively. The exogenous parameter that drives the different profits for Bank B is $\bar{r}$, which we denote respectively by $\bar{r}_+$ and $\bar{r}_0$, where $\bar{r}_+ > \bar{r}_0$. As one would expect, the greater the borrower surplus $\bar{r}$, the higher the lender's profits. Panel A (left) depicts Bank A's pricing strategy $r^A(s)$, which is decreasing, while the right panel plots Bank B's CDF of its rates $F^B(r)$. We also plot the two signal cutoffs—$\hat{s}$, at which Bank A's strategy hits $\bar{r}$, and x, at which Bank A exits.

Figure 2 highlights a key difference between the two types of equilibrium that can arise, one with $\pi^B = 0$—we call it the zero-weak equilibrium as the weak bank earns no profits—and the other with $\pi^B > 0$—we call it the positive-weak equilibrium as the weak bank makes positive profits. As shown, if $\pi^B = 0$ Bank A has a point mass at $\bar{r}_0$ (corresponding to $s \in (x_0, \hat{s}_0)$) but Bank B does not, while if $\pi^B = 0$ the opposite holds. This reflects the fierce competition at the interest rate cap, which echos the last point in Lemma 1 (otherwise, lenders will undercut each other at this point).

3.2 Solving for the Equilibrium Profit of Bank B

We now solve for Bank B's equilibrium profit which pins down the entire equilibrium given the results in Section 3.1. First, define s_A^{be} to be the specialized signal under which Bank A quotes $\bar{r}$ and breaks even (therefore the superscript "be"). Formally, using $\pi^A(\cdot)$ given in (9) and using the

affect $F^B(\cdot)$ indirectly via the endogenous $s^A(r)$.

strategic response of Bank B in Eq. (22), s_A^{be} is the unique solution to the following equation

$$0=\pi^A\left(\overline{r}\left|s_A^{be}\right.\right)=p_{HH}\frac{\int_0^{s_A^{be}}t\phi\left(t\right)dt}{q_s}\cdot\left[\mu_{HH}s_A^{be}\left(1+\overline{r}\right)-1\right]+p_{HL}\left[\mu_{HL}s_A^{be}\left(1+\overline{r}\right)-1\right]. \tag{23}$$

As shown in footnote 14, (23) admits a unique solution inside the interval $(0,1)$. Define s_B^{be} similarly; taking B's payoff function in (12) and setting r to $\overline{r}$, s to s_B^{be}, and π^B to zero give us:[14]

$$0=\pi^B\left(r=\overline{r};s=s_B^{be}\right)=p_{HH}\left[\mu_{HH}\left(\int_0^{s_B^{be}}t\phi(t)dt\right)(1+\overline{r})-\Phi\left(s_B^{be}\right)\right]+p_{LH}\left[\mu_{LH}q_s\left(1+\overline{r}\right)-1\right]. \tag{24}$$

As shown by Lemma 2, the relative ranking between s_B^{be} and s_A^{be} fully determines π^B and $\hat{s}$. Intuitively, the sign of π^B depends on which lender—when quoting $\overline{r}$—hits zero profit first as s decreases. If $s_A^{be}<s_B^{be}$ then Bank B hits zero profit first, and this supports the equilibrium with $\pi^B=0$ with $\hat{s}=s_B^{be}$; otherwise, we have $\pi^B>0$ with $\hat{s}=s_A^{be}$.

Lemma 2. *Given s_A^{be} defined in (23), the equilibrium Bank B profit is*

$$\pi^B=\max\left\{\left[p_{HH}\mu_{HH}\int_0^{s_A^{be}}t\phi\left(t\right)dt+p_{LH}\mu_{LH}q_s\right]\left(1+\overline{r}\right)-\left(p_{HH}\Phi\left(s_A^{be}\right)+p_{LH}\right),0\right\}.$$

When $s_B^{be}<s_A^{be}$ we are in the positive-weak equilibrium in which the weak Bank B makes a positive profit, and $x=\hat{s}=s_A^{be}$. Otherwise, when $s_B^{be}\geq s_A^{be}$ we are in the zero-weak equilibrium where Bank B earns zero profits, with $x<\hat{s}=s_B^{be}$.

3.3 Credit Market Equilibrium

Credit market equilibrium characterization. The next proposition provides a full analytical characterization of the credit market equilibrium with specialized lending. Appendix A.3 generalizes the equilibrium characterization for the case of non-zero recovery.

Proposition 1. ***(Credit Market Equilibrium)*** *In the unique equilibrium, Bank A follows a pure strategy as in Definition 1. In this equilibrium, lenders reject the borrower upon a low general signal realization $h^j=L$ for $j\in\{A,B\}$. Otherwise (i.e., when $h^j=H$), their strategies are characterized as follows, with the equilibrium π^B given in Lemma 2.*

[14] There are several points to make. First, regarding the definition of s_B^{be}, the rate r in (12) is $r^A(s)$; we essentially separate rate r and s in (24). Second, for s_A^{be}, technically speaking in (23) Bank A quotes $\overline{r}^-$ so that $1-F^B\left(\overline{r}^-\right)=\frac{1}{q_s}\int_0^{s_A^{be}}t\phi\left(t\right)dt$, as (22) requires $r\in[\underline{r},\overline{r})$. Finally, we have a unique solution of (23) because $\pi^A\left(\overline{r}\left|s_A^{be}\right.\right)$ is strictly increasing in s_A^{be}, with $\pi^A\left(\overline{r}\left|s_A^{be}=0\right.\right)<0$ and $\pi^A\left(\overline{r}\left|s_A^{be}=1\right.\right)=p_{HH}\left[\mu_{HH}\left(1+\overline{r}\right)-1\right]+p_{HL}\left[\mu_{HL}\left(1+\overline{r}\right)-1\right]>0$; the latter is implied by Bank A's willingness to make an offer given $g^A=H$.

1. *Bank A with a specialized signal s offers*

$$r^A(s) = \begin{cases} \min\left\{\frac{\pi^B + p_{HH}\Phi(s) + p_{LH}}{p_{HH}\mu_{HH}\int_0^s t\phi(t)dt + p_{LH}\mu_{LH}q_s} - 1, \overline{r}\right\} & \text{for} \quad s \in [x,1], \\ \infty, & \text{for} \quad s \in [0,x). \end{cases} \tag{25}$$

The equation pins down $\underline{r} = r^A(1)$. *If* $s \in (\hat{s}, 1]$ *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*

$$F^B(r) = \begin{cases} 1 - \frac{\int_0^{s^A(r)} t\phi(t)dt}{q_s} & \text{for} \quad r \in [\underline{r}, \overline{r}) \\ 1 - \mathbf{1}_{\{\pi^B = 0\}} \cdot \frac{\int_0^{\hat{s}} t\phi(t)dt}{q_s} & \text{for} \quad r = \overline{r} \end{cases}, \tag{26}$$

where $\mathbf{1}_{\{X\}} = 1$ *if* X *holds and is zero otherwise. When* $\pi^B = 0$, $F^B(\overline{r}) = F^B(\overline{r}^-)$ *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* $\overline{r}$*.*

The proof for Proposition 1 mainly covers three theoretical issues. First, we show that the specialized lender always adopts a pure strategy in any equilibrium; that is to say, Bank A's pure strategy, which is implicitly taken as given in Definition 1, is a result rather than an assumption. Second, we prove that the FOC conditions used in the equilibrium construction detailed in Section 3.1 are sufficient to ensure global optimality. Third, somewhat surprisingly, thanks to the endogenous adjustment of π^B and $\underline{r}$, we never need to "iron" a la Myerson (1981) in the interior range for equilibrium interest rates. In fact, consistent with point 3 in Lemma 1, Bank A's quotes never bunch at some endogenous threshold—except at the exogenous rate cap $\overline{r}$ when the zero-weak equilibrium ensues.

Properties of credit market equilibrium. Figure 3 illustrates the main properties of the credit market equilibrium with specialized lenders. For exposition purposes, we assume that Bank A's specialized signal s is obtained from observing $\theta_s + \epsilon$, so that

$$s = \mathbb{E}\left[\theta_s | \theta_s + \epsilon\right], \tag{27}$$

where $\epsilon \sim \mathcal{N}(0, 1/\tau)$ indicates a white noise, with precision parameter τ, which captures the signal-to-noise ratio of Bank A's specialized information technology.

The top two panels in Figure 3 plot both lenders' pricing strategies conditional on making an offer; Panel A is the same as that in Figure 2 for convenience while Panel B plots the density $F^{B\prime}$ for Bank B.

Formally, we call Bank A's strategy of $r^A(s)$ decreasing in s "private-information-based pricing," which has important implications on the equilibrium interest rate differentials studied in Section 4. When Bank A's private assessment of borrower quality is sufficiently low, i.e., $s < x$, it rejects

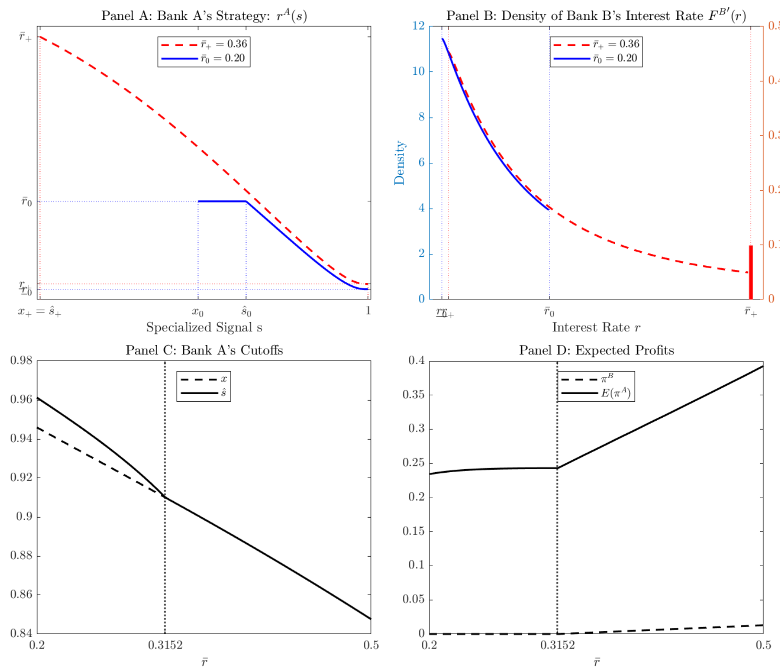

Figure 3: **Equilibrium strategies and profits.** In the top two panels, we plot equilibrium strategies for both lenders. Panel A depicts $r^A(s)$ as a function of s and Panel B plots $F^{B'}(r)$ for as a function r; strategies with $\bar{r}_+$ are depicted in red dashed lines while strategies with $\bar{r}_0$ are depicted in blue solid lines. 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. Parameters: $q_g = 0.75$, $q_s = 0.95$, $\alpha_u = \alpha_d = \alpha = 0.85$, and $\tau = 1$, where τ captures the signal-to-noise ratio of Bank A's specialized information technology as $s = \mathbb{E}[\theta_s | \theta_s + \epsilon]$ and $\epsilon \sim \mathcal{N}(0, 1/\tau)$.

the borrower. Panel C further plots the two specialized signal cut-offs for Bank A, i.e., $\hat{s}$ at which it starts quoting $\bar{r}$ and x at which it starts rejecting the borrower.

Finally, Panel D plots the expected profits—$\mathbb{E}(\pi^A)$ and π^B—for the two lenders, against the exogenous interest rate cap $\bar{r}$. Recall that $\bar{r}$ can also be interpreted as the return of a good project, capturing the surplus to be realized from a loan. Thus, a higher total surplus gives rise to less fierce competition, and as a result, both lenders—including the weak lender B—make positive expected profits upon a favorable general signal H. This explains Panel D, which shows that π^B is strictly positive for sufficiently high values of $\bar{r}$. Put differently, the model features a positive-(zero-) weak equilibrium when $\bar{r}$ is relatively high (low).

For a better illustration, consider the competition at interest rate $\bar{r}$. In the positive-weak equilibrium (high $\bar{r}$'s), the non-specialized Bank B has a point mass on this interest rate, enjoying some "local monopoly power" in competition as it is the only lender in the market when Bank A rejects the borrower upon $s < \hat{s} = x$. This is possible because when the project's surplus (captured by $\bar{r}$) is sufficiently large, the non-specialized lender B is still profitable by quoting $\bar{r}$ despite the winner's curse. We highlight that the weak lender's profits come from its conditionally independent private signal, which could also arise in canonical models; the weak lender's "local monopoly power," however, is a unique feature of our model that arises from Bank A's informed pricing to withdraw. (This point will be elaborated on in Section 4, especially footnote 18 when we discuss the "private-information-bsaed pricing effect.") In contrast, in the zero-weak equilibrium (low $\overline{r}$'s), the specialized Bank A, with a point mass at $\overline{r}$ (when $s \in (x, \hat{s})$, as shown in Panel C), is the monopolistic lender while the nonspecialized Bank B withdraws.

4 Specialized Lending: Interest Rate Wedge

As suggested by Figure Figure 1, the loans on the balance sheets of specialized lenders tend to have higher quality and lower interest rates. Specialized lenders with informational advantage are extending higher quality loans in our model, which is a robust prediction of any information-based model, including those canonical ones à la Broecker (1990) and Marquez (2002). In what follows, we focus on the implications of the model on interest rates.

We define the "interest rate wedge" as the difference between the rates of loans made by specialized and non-specialized lenders. In Section 4.1 we first stress the difference between bids and winning bids on granted loans, which explains why canonical models struggle to generate this empirical regularity (Section 4.2). Then, in Section 4.3, we explain how our private-information-based pricing mechanism helps generate the negative interest rate wedge observed in practice and for which we offer detailed evidence based on Y-14 supervisory data in Section 4.4.

4.1 Interest Rate Wedge: Bids vs. Winning Bids

An economist observes the bank loans granted that the borrowers accept. Put differently, the loans we use to calculate loan interest rates are already on the book of the lender who has won the bidding competition for the loan. In our setting, when Bank A makes a loan offer ($r^A < \infty$), it is accepted by the borrower if $r^A < r^B \leq \infty$—either if there is no offer from Bank B (e.g., when $h^B = L$ so $r^B = \infty$) or Bank A's rate is lower than that offered by Bank B. Therefore, the theoretical counterpart of negative rate differentials in Figure 1 is

$$\Delta r \equiv \underbrace{\mathbb{E}\left[r^A \middle| r^A < r^B \leq \infty\right]}_{\text{interest rate of } A\text{'s granted loan}} - \underbrace{\mathbb{E}\left[r^B \middle| r^B < r^A \leq \infty\right]}_{\text{interest rate of } B\text{'s granted loan}} < 0, \tag{28}$$

where $\{r^i < r^j \leq \infty\}$ denotes the event that Bank i wins the loan.

We call Δr in Eq. (28) the interest rate wedge. There is a crucial difference between the interest rate wedge calculated from "bids," i.e., banks' offered interest rates, and the one calculated from "winning bids," i.e., banks' rates on their granted loans. The winning bid is a first-order statistic (i.e., the smaller one given two quotes). In our context of lending competition, banks can simply reject loan applications by quoting ∞ due to the winner's curse. Therefore, the winning bid necessarily requires $r^i < \infty$, which is implied by the conditioning in Eq. (28).

In summary, although the winner's curse pushes the less informed Bank B to bid higher (often in the form of withdrawals by quoting $r = \infty$), it also leads to higher winning bids from the more informed Bank A. An example from He, Huang, and Zhou (2023) illustrates this point

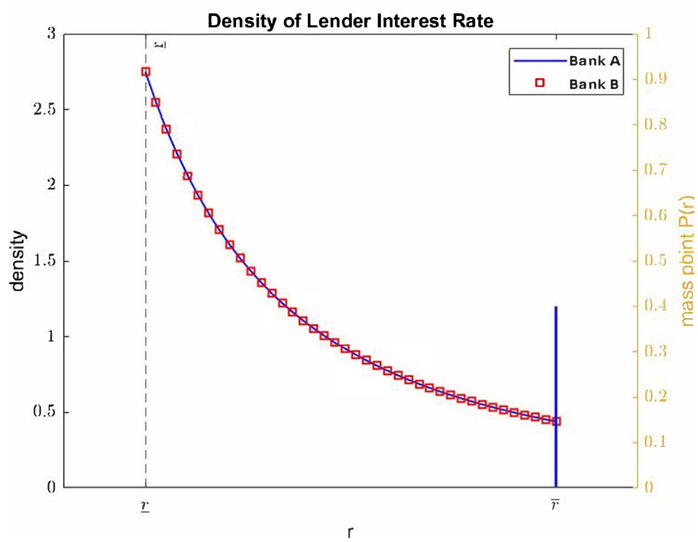

Figure 4: **Example of Lender Bidding Rates in Canonical Models.** We plot the density functions (left scale) and probability mass points (right scale) of lenders' interest rate offer upon favorable signals in He, Huang, and Zhou (2023). Our framework nests He, Huang, and Zhou (2023) by setting $q_s = 1$ (degenerate specialized information), $\alpha_A^u = \alpha_B^u = 1$ (bad-news information structure) and $\alpha_A^d > \alpha_B^d$ (Bank A has better information technology). Here, the endogenous lower bound for rates is $\underline{r} \equiv (1-q)\left(1-\alpha_d^B\right)/q$.

starkly. There, banks are endowed with general signals only, which, for simplicity, follow a bad news structure, that is, $\alpha_u^j = 1$ and $\alpha_d^j < 1$ so that only false positives can occur. In addition, banks differ in the precision of their signals. To capture the idea of specialization, suppose that $\alpha_d^A > \alpha_d^B$ so Bank A is relatively more informed. For illustration purposes, our analysis is conditional on both lenders making offers (i.e., on two H general signals).

As shown in He, Huang, and Zhou (2023), the equilibrium CDF of offered rates for both banks, denoted by $\hat{F}(\cdot)$, coincides in the interior of the common support $r \in [\underline{r}, \overline{r})$, with

$$\hat{F}(r) \equiv \mathbb{P}(\tilde{r}_A < r) = \mathbb{P}(\tilde{r}_B < r) = \frac{r - \frac{1-q}{q}\left(1-\alpha_d^B\right)}{r - \frac{1-q}{q}\left(1-\alpha_d^B\right)\left(1-\alpha_d^A\right)}.$$

Figure Figure 4 plots the bidding strategies of both lenders in He, Huang, and Zhou (2023). As one can see, their densities coincide in the interior of their support. The only difference in the lenders' strategies is at the upper limit $\overline{r}$. Bank A quotes the monopolistic rate $r = \overline{r}$ with a positive mass $1 - \hat{F}(\overline{r}^-) > 0$ while Bank B rejects the borrower by quoting $r = \infty$ with the same probability. Consistent with the intuition of the winner's curse, the bidding rates of the less informed Bank B are higher than those of the more informed Bank A (i.e., $\infty > \overline{r}$ implies first-order stochastic dominance). However, one can formally show that the interest rate wedge calculated from winning bids goes the opposite way. In these events, Bank A earns a monopolistic profit $r^A = \overline{r}$ (which is counted in the winning bids) while Bank B rejects (quoting $r^B = \infty$ which is not counted in the winning bids).[15]

[15] This discussion only concerns the event of participation from both lenders. In this case, one can formally prove

Because Bank A's monopoly rent comes from its informational advantage, we call this economic force the "information rent" effect, which favors a positive interest rate wedge $\Delta r > 0$. In contrast, our model also features the "private information-based pricing" effect discussed in Section 3.3 (after Figure 3), which favors a negative interest rate wedge $\Delta r < 0$. The next sections discuss these two effects in isolation by studying two classes of models separately.

4.2 Canonical Models: The Information Rent Effect

Canonical credit market competition models parameterize the information technology by the signal's precision that captures the lenders' ability to screen out uncreditworthy borrowers. There, the most natural way to capture "specialized lending" is by imposing asymmetric screening abilities on general signals (assuming a degenerate specialized fundamental state that always equals one) along the line of Marquez (2002); He, Huang, and Zhou (2023), as illustrated in Figure 4.

Specification in canonical models. Regarding the specific information structure of general signals given in (3)), the literature has primarily focused on the following two parameterizations. The first is the bad news structure adopted in He, Huang, and Zhou (2023) assuming that $\alpha_d^A > \alpha_d^B$ (and $\alpha_u^A = \alpha_u^B = 1$), based on which we produce Figure 4. Alternatively, Marquez (2002) and He, Jiang, and Xu (2024) adopt a symmetric information structure in which $\alpha_u^A = \alpha_d^A > \alpha_u^B = \alpha_d^B$. In the bad news structure, Bank A makes fewer false positive mistakes than Bank B, while in the symmetric information structure, A makes fewer false positive and false negative mistakes than B. For ease of exposition, in both cases, we use $\alpha^A > \alpha^B$ to denote Bank A having a more informative (binary) signal.

As emphasized before, in these canonical models, only quantity decisions (i.e., whether to lend or not) are based on the signal realizations, while pricing decisions (offered interest rates) are randomized. We have the following proposition.

Proposition 2. ***(Counterfactual Prediction in Canonical Models.)*** *In the canonical models of bank competition with unidimensional information:*

1. *Under a bad news structure, there exists a threshold $\hat{\bar{r}}$ such that $\Delta r > 0$ for $\bar{r} < \hat{\bar{r}}$;*
2. *Under a symmetric information structure, when $\alpha^A = \alpha$ and $\alpha^B \uparrow \alpha$, $\Delta r > 0$ for $\bar{r} \leq \frac{1}{q} - 1$ or $q \geq 1 - \alpha + \alpha^2$.*

In general, since Bank A's private signal is more precise, the weak lender B is more concerned about the winner's curse, that is, picking up a "lemon" which the competitor lender rejected. As a result, B randomly withdraws even after receiving a favorable signal $g^B = H$, effectively making

that $\Delta r > 0$. However, from an unconditional perspective, we also need to take into account the possibility of an unfavorable general signal under which each lender quotes $r = \infty$. Given a bad news structure, the stronger Bank A is more likely to receive an unfavorable general signal (which is truth-revealing) and therefore reject the loan. This force complicates the analysis. We show in Proposition 2 that $\Delta r > 0$ when $\bar{r}$ is sufficiently small (i.e., when loan rejection occurs often in equilibrium). Nevertheless, when discussing the result in Proposition 2 we point out that the threshold of $\bar{r}$ is too large to be relevant in practice.

Bank A a monopolist. This exactly corresponds to the *information rent* effect, mentioned right after Figure 3, driving the specialized Bank A to have higher expected winning bids (that is, rates on granted loans) than Bank B. This force pushes the model to deliver a positive interest wedge.

The first part of Proposition 2 concerns the bad news structure; there, the effect of information rent intensifies (and therefore $\Delta r > 0$) if the weak lender rejects borrowers more often in equilibrium. The lower the exogenous interest rate cap $\bar{r}$, the more severe the winner's curse, and hence the weak lender is more likely to reject its loan applications; this explains the first part of Proposition 2 so that $\Delta r > 0$ when $\bar{r}$ is below a certain threshold $\hat{\bar{r}}$. As we will explain soon, the threshold is way above the interest rate cap of usury rate in the U.S., under empirically relevant parameters calibrated to the U.S. banking industry.

The second part of Proposition 2 concerns the symmetric information structure. We are unable to formally prove the general case. Instead, we consider only the limiting case of $\alpha^B \uparrow \alpha^A$. As explain below, the two calibrated precision parameters are extremely close to each other ($\alpha^A = 0.984$ and $\alpha^B = 0.977$), confirming that this limit is empirically relevant. What is more, the information rent effect is presumably stronger when the gap in information technology $\alpha^A - \alpha^B > 0$ widens, which we will demonstrate in our numerical examples in Figure 5.

Calibrations and numerical examples. We now show that the canonical model delivers the counterfactual prediction of $\Delta r > 0$ under empirically relevant primitives that are calibrated to U.S. banking data. The key steps of our calibration are given below, while a more detailed description is available in Appendix A.5.

We set $\bar{r}$ to be 36%, the rate cap imposed by most U.S. usury laws. There are three other key parameters in canonical models: two signal precision parameters α^A and α^B, and the loan quality prior q. We calibrate these parameters on the basis of three empirical moments. First, using Y14Q.H1 data for stress-tested banks, we calculate the non-performing loan (NPL) rates of specialized and non-specialized banks in our sample. This gives an NPL rate of 3% for specialized banks and 4% for non-specialized banks, as reported in Table B.1 in Section B. The third empirical moment is the loan approval rate in U.S. banks. Chart 11 in DeSpain and Pandolfo (2024) reports loan approval rates across banks with different sizes; to be consistent with the Y14Q.H1 data, which covers large stress-tested banks, we take the loan approval rate for large banks, which is about 50% in the past seven years.

We then calculate the model-implied moments based on canonical models, which allows us to back out the three primitive parameters of interest. For example, the NPL rate of the specialized lender is $\mathbb{P}\left(\theta = 0 \middle| r^A < r^B < \infty\right)$, which equals 3% in the data. The overall loan approval rate 50%, which is presumably averaged between both types of banks, requires a bit more care. As there is no data on loan applications to specialized versus non-specialized lenders, we match the overall loan approval rate, which in our model is given by $\frac{1}{2}\mathbb{P}(g^A = H) + \frac{1}{2}\mathbb{P}(g^B = H)F^B(\bar{r})$. For the bad-news structure, the calibrated parameters are $\alpha^A = 0.984$, $\alpha^B = 0.977$, and $q = 0.506$; under these parameters, we have $\Delta r = 0.26\%$. For the symmetric information structure, we have

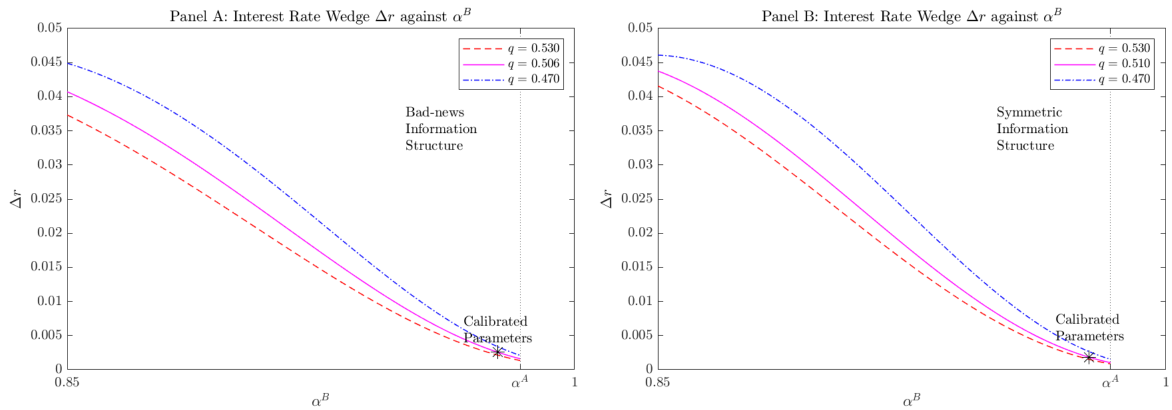

Figure 5: **Interest Rate Wedge under canonical models.** We plot the interest rate wedge $\Delta r = \mathbb{E}\left[r^A \middle| r^A < r^B \leq \infty\right] - \mathbb{E}\left[r^B \middle| r^B < r^A \leq \infty\right]$ with calibrated parameters, under different information structures. We fix $\bar{r} = 0.36$ at the usury rate and calibrate α^A, α^B, and q based on moments of nonperforming loan rate of specialized and non-specialized banks ($NPL^A = 3\%$ and $NPL^B = 4\%$, and loan approval rate 50%. We highlight the calibrated parameters in each panel with marker "x" and study comparative statics of α^B and q. Panel A depicts Δr as a function of α^B while varying q under the bad-news information structure, with calibrated parameters being $\alpha^A = 0.984$, $\alpha^B = 0.977$, $q = 0.506$. Panel B depicts Δr as a function of α^B while varying q under the symmetric-information structure, with calibrated parameters being $\alpha^A = 0.984$, $\alpha^B = 0.977$, and $q = 0.510$.

$\alpha^A = 0.984$, $\alpha^B = 0.977$, and $q = 0.510$, under which $\Delta r = 0.17\%$.

We plot the implied interest rate wedge in Figure 5 using these baseline parameters, together with comparative statics when varying α^B and q. In Panel A in Figure 5 which concerns the bad-news structure, we plot Δr—which is always positive in the figure—as a function of α^B, for three levels of q. The calibrated parameters are denoted by the "*" marker in the figure. Recall that Proposition 2 states that $\Delta r > 0$ holds as long as the interest rate cap $\bar{r}$ is not too high. The relevant question then is: How large should the interest rate cap be so that Δr becomes negative? Given the calibrated parameters, the answer is 393%, which is significantly higher than the current in U.S. usury rate of 36%.[16]

In Panel B in Figure 5, we turn to the symmetric-information structure. There, we also observe positive interest rate wedges as a function of α^B. One can verify that Condition 1 in Part 2 of Proposition 2 is indeed true under the calibrated parameters, so the implied interest rate wedge must be positive *even when* $\alpha^B \uparrow \alpha^A$. Note that the two calibrated precision parameters are extremely close to each other in Panel B of Figure 5 , so the limit of Proposition 2 is empirically relevant. Presumably, the effect of the information rent is stronger when the gap in the information technologies $\alpha^A - \alpha^B > 0$ is larger, which is confirmed not only in Panel B of Figure 5, but also in all our numerical exercises.

[16]For more details, see "Calibration" in Appendix A.5 on Page 50.

Calibration with non-zero recovery rate Finally, so far we have assumed a zero recovery for defaulted loans while in practice they typically have non-zero recovery. As explained toward the end of Section 2.3, we provide a full characterization of equilibrium with non-zero recovery $\delta \in (0, 1)$ for models with specialized lending as well as the canonical settings. We set $\delta = 0.6$ which is approximately the average recovery rate in the Y-14 data (including all types of collateral). We then recalibrate our three parameters in the canonical models and confirm that the implied interest rate wedge, though smaller, is still positive.[17]

Two important conceptual points are worth mentioning. First, if δ's are heterogeneous in the data, then borrowers with lower recovery rates are more likely to be rejected, yielding the observable recovery rate 0.6 to be an overestimate of δ in the model due to selection. Second, when δ is higher, the equilibrium interest rate wedge is expected to be smaller as the equilibrium rates are lower. However, low interest rate levels do not necessarily imply a negative interest rate wedge; to the extreme of $\delta = 1$ the model converges to perfect Bertrand competition and the resulting interest rate wedge converges to zero.

Combining Proposition 2, Figure 5, and our calibration results for the non-zero recovery case, we conclude that canonical models generate counterfactual implications on the interest rate wedge. As we show below, our model with an additional specialized signal naturally delivers this result.

4.3 Our Model: The Private-Information-Based Pricing Effect

We have illustrated by Panel A in Figure 2 that the "private-information-based pricing" effect implies that i) Bank A with a more favorable specialized signal offers a lower rate and ii) rejects the borrower when s falls below a certain threshold x). This naturally pushes us closer to obtaining a negative interest rate wedge.

However, the early discussion regarding "bids versus winning bids" around Figure 4 suggests that whether Bank B rejects (quoting $r^B = \infty$) or not plays a role. As discussed, counterfactual prediction $\Delta r > 0$ is more likely to occur if Bank B rejects more often (so Bank A enjoys a higher information rent). Hence, the effect of private-information-based pricing is more likely to prevail in a positive-weak equilibrium where Bank B never rejects after receiving a high signal and it even enjoys some "local monopoly power" as the only lender (when Bank A withdraws after $s < x$) having a point mass at $\bar{r}$. Note that this point mass is the distinct feature of our model with a private specialized signal compared to canonical settings a la Broecker (1990).[18] As a result, when Bank B never withdraws from competition after receiving $g^B = H$, the better informed Bank A

[17] For the bad-news (symmetric) information structure, to match the observed moments—i.e., NPL ratios of 0.3 and 0.4 for specialized and non-specialized lenders, and 0.5 approval rate, the calibrated parameters are $q = 0.4967$ (0.5006), $\alpha^A = 0.9846$ (0.9843), $\alpha^B = 0.9788$ (0.9790) which yield a negative interest rate wedge of $\Delta r = 5 \times 10^{-4}$ (4×10^{-5}).

[18] In canonical models, although the weak bank may earn some positive profits given a high borrower surplus (say large q and $\bar{r}$), it never has a point mass at $\bar{r}$ to enjoy "local" monopoly power. To see the intuition, note that because in canonical settings information is used to determine participation, the strong lender never withdraws upon H; and since only one lender can have a point mass at $\bar{r}$ (a result that is similar to Lemma 1 for canonical models), it must indeed be the strong lender who possesses such a point mass.

undercuts rates to win higher quality borrowers while leaving those lemons to Bank B (who then makes loans with higher winning bids).

Is $\pi^B > 0$ a necessary condition for $\Delta r < 0$? A special case. The discussion above suggests that a profitable weak bank is necessary for a negative interest rate wedge. This is not true. The following proposition focuses on the special case of $\overline{r} = \infty$, and considers a degenerate general fundamental (so Bank B is uninformed) and a uniformly distributed specialized signal.

Proposition 3. ***(A Special Case of Uniform Distribution)*** *Suppose $\overline{r} = \infty$ so that rejection is off equilibrium, general signals are degenerate ($q_g = 1$ or $\alpha_u = \alpha_d = 0.5$), and the specialized signal's distribution follows $\phi(s) = 1+\epsilon\left[2 \cdot \mathbf{1}_{s \le 0.5} - 1\right]$. In equilibrium, i) $\pi^B = 0$ always, ii) $\Delta r = 0$ when $\epsilon = 0$ (i.e., $s \sim \mathbb{U}[0, 1]$), and iii) $\Delta r > 0$ ($\Delta r < 0$) when $\epsilon > 0$ ($\epsilon < 0$) for infinitesimal ϵ.*

Several important implications of this proposition follow. First, $\pi^B > 0$ is not necessary for $\Delta r < 0$, as we have $\pi^B = 0$ always for the uninformed Bank B. Intuitively, when $\overline{r} = \infty$, B never withdraws in equilibrium regardless of its profit. As discussed after Figure 4, it is the endogenous withdrawal from the weaker bank—not profitability per se—that plays a key role in driving the difference between bids and winning bids.

Second, when the specialized signal follows a uniform distribution (together with a degenerate general signal and $\overline{r} = \infty$), the two aforementioned effects, information rent and private information-based pricing, equalize, and lenders have the same winning bids on their granted loans. Then, starting from this benchmark, any tilting toward private-information-based pricing—e.g., tilting more probability mass toward favorable specialized signals and therefore lower rates—would generate a negative interest rate wedge observed in the data.

Comparative statics on interest rate wedge. Figure 6 plots the comparative statics of the interest rate wedge Δr with respect to the model parameters, with regions of zero-weak and positive-weak equilibria highlighted. Just as in the calibration exercise for canonical models detailed in the discussion around Figure 5, we now choose our parameters α, q_g and q_s (given in the caption in Figure 6) to fit the three empirical moments (NPL ratios in specialized and non-specialized lenders which are 3% and 4% respectively, and loan approval rate 50%).[19] Implicitly, we fix $\overline{r} = 36\%$ and $\tau = 1$, but our results are robust to these choices. Importantly, as shown in Figure 6 (marked with $*$), our model generates a negative interest rate wedge under the calibrated parameters.

The top two panels (A and B) concern information technology parameters α (precision of general signals) and τ (precision of the specialized signal). The overall pattern is that when information technology improves—either the general signal precision α (Panel A) or the specialized signal precision τ (Panel B)—the economy is more likely to be in the zero-weak equilibrium where

[19] We need to adapt the formula for model-implied moments to the model with specialized signal. For instance, since Bank A upon $g^A = H$ will also reject loan applications for sufficiently low signal realizations, the model-implied loan approval rate becomes $\frac{1}{2}\mathbb{P}(g^A = H)(1 - \Phi(x)) + \frac{1}{2}\mathbb{P}(g^B = H)F^B(\overline{r})$.

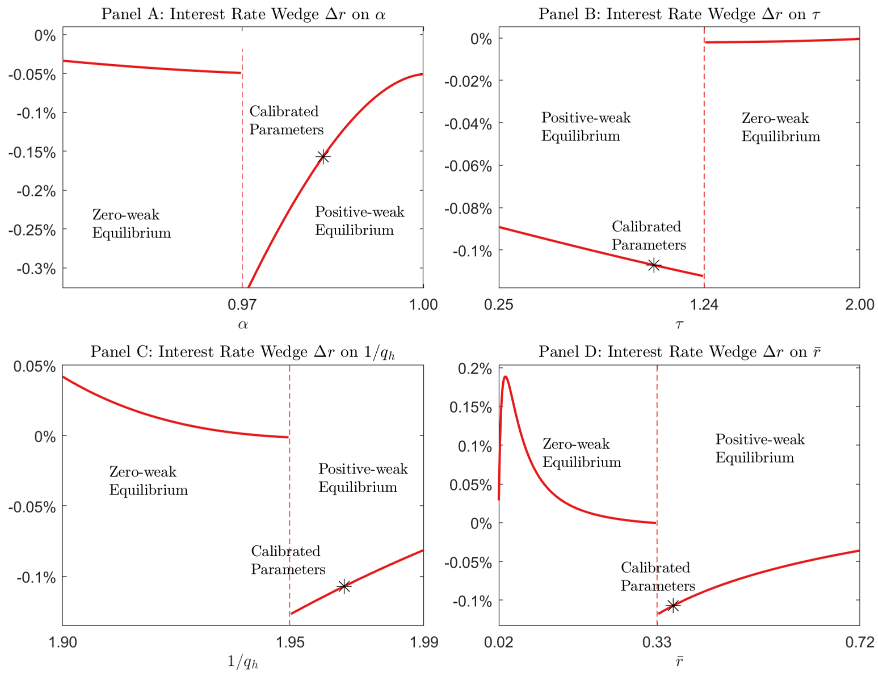

Figure 6: **Interest rate wedge.** Panel A to Panel D depict $\Delta r = \mathbb{E}\left[r^A \middle| r^A < r^B \leq \infty\right] - \mathbb{E}\left[r^B \middle| r^B < r^A \leq \infty\right]$ as a function of α, τ, $1/q_g$ and $\bar{r}$. In Panel C, we vary $1/q_g$ but fixing the project success probability q, i.e., setting $q_s = q/q_g$. The positive-weak equilibrium arises when τ lies below a certain value and $1/q_g$ and $\bar{r}$ exceed a certain value. Baseline calibrated Parameters: $\bar{r} = 0.36$, $q_g = 0.508$, $q_s = 0.990$, $\tau = 1$ and $\alpha_u = \alpha_d = \alpha = 0.986$. Note τ captures the signal-to-noise ratio of Bank A's specialized information technology as $s = \mathbb{E}\left[\theta_s | \theta_s + \epsilon\right]$ and $\epsilon \sim \mathcal{N}(0, 1/\tau)$.

the nonspecialized Bank B is sufficiently "weak" and hence makes zero profits. Note that Δr is discontinuous when π^B becomes zero, since Bank B reallocates a probability mass of $1 - F^B(\bar{r}^-) > 0$ from $\bar{r}$ to ∞ (see also Panel B in Figure 3).

Therefore, an improvement in signal precision tends to weaken the non-specialized lender even further. To see the intuition, observe that i) a higher general signal precision α levels the playing field on general information and hence effectively enlarges the specialized information advantage of Bank A, and ii) a higher specialized signal precision τ directly boosts Bank A's information advantage. Since the effect of private-information-based pricing tends to dominate in a positive-weak equilibrium, a sufficiently low information technology parameter helps deliver $\Delta r < 0$.

Panel C conducts another comparative static analysis that captures the relative importance of general versus specialized information. More specifically, consider varying $1/q_g$ but fixing the project success probability q, which implies $q_s = q/q_g$. The companion paper by He, Huang, and Parlatore (2024) explains that this comparative static exercise corresponds to the scenario in which general signals increase their span so that they cover more fundamental states critical to the success of the funded project.[20] Interestingly, this exercise yields an opposite comparative statics

[20] As explained in Section 2.3 where we introduce multi-dimensional fundamental states, He, Huang, and Parlatore (2024) interpret $\theta_g \equiv \prod_{n=1}^{\hat{N}} \theta_n$ ($\theta_s \equiv \prod_{n=\hat{N}+1}^{N} \theta_n$) as the borrower's "hard" ("soft") fundamental state, and model the expansion of the span of "hard" information by an increase in $\hat{N}$ (so θ_g covers more fundamental states). In the

to the standard information technology parameters (α and τ in the top two panels) modeled as signal precision. Intuitively, now Bank B, equipped with general information that covers more fundamental states, becomes relatively stronger (rather than weaker when α and/or τ increase), so the credit market equilibrium is more likely to be in the region of positive-weak (and delivers a negative interest rate wedge). Motivated by recent advances in big data technology, He, Huang, and Parlatore (2024) employ this framework to study the concept of "hardening soft information."

Finally, Panel D studies the rate cap $\bar{r}$ which also captures the total surplus in this economy. When the total surplus increases, the credit market equilibrium moves to the positive-weak region, which is intuitive. We observe that Δr jumps down to be negative first, then increases and becomes even positive when $\bar{r}$ is sufficiently high. This is consistent with Proposition 3, in that the sign of Δr does not depend on the sign of π_B. This result highlights the robustness of our mechanism of private-information-based pricing.

As a robustness check, we also calibrate our model with specialized lending for a positive recovery $\delta = 0.6$ (for a full equilibrium characterization, see Appendix A.3). The new calibrated parameters are $\alpha = 0.9870$, $q_g = 0.5012$, $q_s = 0.9897$; and consistent with the main prediction of our paper, the resulting interest rate wedge is negative (-1×10^{-4}).

4.4 Lower Rates and Better Performance: Empirical Evidence

The two main testable predictions of our model relate to differences in loan pricing and performance between specialized and non-specialized banks. We show supporting evidence for these predictions, based on raw differences, in Figure 1. In this section, we conduct a more rigorous empirical analysis of these two testable hypotheses.

Our empirical study uses the supervisory data collected by the Federal Reserve System (Y14Q-H.1) which covers all C&I loans (over one million USD) to which a stress-tested bank has committed between 2012 and 2023. In Appendix B, we provide more details on the data, variable construction, and regression specifications.

In our model a bank is either specialized or not, while in the data bank specialization can take a continuum of values as measured by "excess specialization" in Blickle, Parlatore, and Saunders (2023). To incorporate their measure into our framework, we identify whether a bank specializes in a particular industry by assigning a binary specialization flag. This flag is set to 1 if "excess specialization" for bank b in industry s, defined in Blickle, Parlatore, and Saunders (2023), exceeds a certain threshold. We set the threshold as 4%, so a bank b is specialized in industry s if it invests 4% more of its C&I lending relative to the overall share of industry s in all C&I lending, i.e.

$$\frac{LoanAmount_{b,s,t}}{\sum_s LoanAmount_{b,s,t}} - \frac{LoanAmount_{s,t}}{\sum_s LoanAmount_{s,t}} \geq 4\%.$$

short-run, this expansion of $\hat{N}$ does not alter the span of the soft signal so that θ_g and θ_s overlap (as both have their own $\hat{N}$'s), but in the long-run the coverage of θ_s also shrinks so that θ_g and θ_s do not overlap. Panel C corresponds to the long-run scenario. For the short-run scenario, the expansion of $\hat{N}$ induces a correlation between θ_s and θ_g, which makes the analysis a bit involved but still tractable. For more details, see He, Huang, and Parlatore (2024).

Table 1: **Interest Rate and Loan Performance**

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank	-0.076***	-0.150***	-0.082***	-0.008***	-0.005***	-0.005***
	[0.006]	[0.007]	[0.007]	[0.001]	[0.001]	[0.001]
Log Loan Amount	-0.156***	-0.170***	-0.178***	-0.000	-0.000*	-0.001**
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Constant	4.992***	5.118***	5.178***	0.045***	0.047***	0.049***
	[0.019]	[0.018]	[0.018]	[0.002]	[0.002]	[0.002]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating Category (1-3) FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	353,544	353,537	351,776	353,544	353,537	351,776

Note: In Columns (1) – (3), we regress the loan rate paid by a firm on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Under this threshold, the average bank specializes in 2.8 industries; the average over-investment is 8.9% for specialized banks, while only 0.2% for non-specialized ones. Our analyses below are robust to using 3% or 5% as a threshold for a specialization (not reported for brevity).

Baseline results. We consider the following specification that relates our variable of interest y_{libst}, either the loan rate or performance, for a bank b's loan l to borrower i in industry s in quarter-year t, to a dummy $Specialized_{bst}$ that denotes whether the bank b in question is specialized in the industry s at time t:

$$y_{libst} = \beta_0 + \beta_1 \cdot Specialized_{bst} + \beta_2 \cdot Size_{lt} + \xi_{bt} + \sigma_{st} + \phi_{lt}^{\text{rating-category}} + \omega_{lt}^{\text{loan-purpose}} + \epsilon_{libst}. \quad (29)$$

The inclusion of controls and fixed effects in (29) deserves further discussion. In our model, loans are of fixed size and have the same purpose; therefore, we control for the loan's size and purpose to ensure that these characteristics do not drive our findings. Also, although firm-fixed effects are usually used in the literature to control for borrower-specific factors that are not time varying, it is inappropriate to include them in our setting. In our model, firms sorting into specialized and non-specialized banks is a key feature of the mechanism that we highlight. Therefore, we should ideally saturate our regression with as many borrower characteristics as possible, say EBIT, ROA, and assets-to-debt. However, more than 75% of the firms in our sample are private firms, for many of which we do not have data on balance sheets or income statements.

To address this issue, in our regression (29) we include the time-varying rating category dummies, which are defined at the loan-time level, to absorb borrower-specific time-varying factors. We calculate each loan's rating category based on banks' internal risk ratings of loans, and some extra care needs to be taken. Our model is conditional on firm characteristics that are *observable* to both lenders; but banks' internal loan risk ratings are potentially private information (though the extent of private information is limited, as they must be defensible to Federal Reserve examiners). We mitigate this issue by classifying the loans as high-risk, mid-risk, and safe based on the internal ratings of the loans; as shown in Appendix Table A.4, for a subsample firms that we do have balance sheet characteristics (e.g., leverage and EBIT/Assets), the three internal risk categories indeed correspond to generally accepted metrics of firm riskiness. By categorizing these risks into broad buckets, we take advantage of the information they convey on the borrower quality, while reducing the likelihood that any unique bank-specific knowledge of the borrower is reflected by them.

Columns (1)-(3) in Table 1 show a negative correlation between banks being specialized and the loan rates they charge in their industry of specialization. We consecutively introduce bank-year and industry-year fixed effects to control for any time-varying heterogeneity among banks and industries. This is the empirical counterpart to the negative interest rate wedge we studied in Section 4. Magnitude-wise, the identified negative wedge (8∼15 bps) is below the raw difference of about 40 bps shown in Figure 1, presumably due to better controls in our richer specification in Eq. (29). Interestingly, the magnitude identified in Table 1 matches squarely with the predicted interest rate wedge under calibrated parameters shown in Figure 6. Finally, there is a significantly negative correlation between specialization and non-performance reported in columns (4)-(6) in Table 1.[21] As one would expect if bank specialization is driven by the banks' informational advantage, which is the key driver of our model, specialized lenders pick higher quality loans, which are less likely to turn non-performing later.

Robustness tests. In Appendix B we offer a series of robustness tests to confirm that our results hold under various specifications. First, Appendix B.3 considers alternative borrower risk measures. Panel A of Table B.3 shows that our results are robust to using dummies for a bank's exact risk assessment on a scale of 1-10 instead of our three broad categories. In Panel B of Table B.3, we also show that our results hold if we use observable firm characteristics, such as EBIT / assets and leverage as risk measures, based on a subset of firms (about half) who report such characteristics in the Y-14 data. Second, in Appendix B.4 we use 4-digit NAICS codes—which yield 310 different industries — as opposed to the 2-digit industries used in baseline to calculate lender specialization. There, we define a lender as specialized if it is 1% or more overinvested.[22] Our results are confirmed using this more stringent definition. Third, Appendix B.5 removes the COVID 19 period (the years

[21]Non-performing loans are those that fall into arrears, are not paid down by the end of their maturity, default or require renegotiation due to covenant violation issues. The average non-performance rate of loans throughout our sample is around 4%.

[22]This cutoff defines the top 20% of all bank lending – i.e. to top quintile of bank-industry-year observations – as specialized. This is equivalent to the logic we used in defining the threshold for specialization at the 2 digit industry-level.

2020 and 2021, which could be affected by a period of unusual market conditions). We show that our coefficients remain qualitatively unchanged in Appendix Table B.5.

Empirical results using SNC data and Dealscan data. Finally, we confirm that our results are valid outside the Y-14 data. Collected by the Federal Reserve, the OCC, and the FDIC, SNC (Syndicated National Credit Registry) data contain information on syndicated loans over 20 million USD in value and which are held by two or more U.S. banks.[23] Compared to the 40 stress tested banks represented in the Y-14 data, the SNC data cover 218 lenders that originate at least one syndicated loan in the U.S. between 1993 and 2018. Hence, one can use it to test whether our predictions hold for a sample that includes smaller lenders. Unfortunately, the SNC data have several serious limitations (which we discuss in detail in Appendix B.6). One key limitation, which is crucial to our study, is that the SNC data do not contain information on the loan interest rates. To overcome these issues, we merge SNC data with Dealscan following a methodology first laid out in Cohen, Friedrichs, Gupta, Hayes, Lee, Marsh, Mislang, Shaton, and Sicilian (2018); the details of this merge are discussed in the Appendix B.6. The merged sample does not represent the universe of loans, and these SNC tests serve as indicative additions to our main analyses. However, Appendix Table A.B.6 confirms our key theoretical predictions: the specialization of the lead arranging bank in a syndicated loan is related to lower rates and better ex-post loan performance.

Multiple specialized lenders in an industry. In general, competitiveness in the loan market in an industry is an important determinant of loan prices. For simplicity, our model considers only one specialized lender; thus, this excludes one empirically relevant mechanism where multiple specialized banks in the same industry may compete on the same borrower.

To ensure that our results are not driven by potential competition among multiple specialized banks, Table 2 expands Table 1 with additional control for a bank operating in an industry with multiple specialized lenders. We define the loan market as having multiple specialized lenders simply as a dummy that takes the value of 1 if two or more banks specialize in a given two-digit industry, and add this dummy and its interaction with "Specialized Bank" to our baseline regression.[24] Under this alternative mechanism, the specialized lender charges lower rates only because it faces fiercer competition from other specialized banks, and therefore the significantly negative effect on "Specialized Bank" in Table 1 would be fully absorbed by the interaction term in Table 2.

Columns (1)-(3) in Table 2 support the economic mechanism proposed by our model. We observe a negative coefficient for the dummy "Multiple Specialized Lenders," potentially because industries with more specialized lenders have better quality borrowers.[25] But the coefficients of the interaction term are either positive or insignificant across all three specifications (Columns (1)-(3)),

[23] In 2018 these thresholds were raised to 100 million USD and three supervised U.S. banks, respectively. We cut our data in 2018 to avoid sample construction issues. Our results are unaffected if we keep years after 2018.

[24] Our results are robust to alternate definitions of this measure, as we show in Appendix B.7.

[25] This hypothesis is further supported by the negative coefficients for "Multiple Specialized Lenders," in columns (4) – (6), where we take the non-performing dummy as the dependent variable.

Table 2: **Interest Rate and Loan Performance: Controlling for Lending Market Competition among Specialized Banks**

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rates			Non-Performing Loans	
Specialized Bank	-0.454***	-0.179***	-0.112***	-0.019***	-0.007	-0.007
	[0.037]	[0.036]	[0.038]	[0.005]	[0.005]	[0.005]
Log Loan Amount	-0.157***	-0.171*	-0.178**	-0.000	-0.001*	-0.001**
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Multiple Specialized Lenders	-0.149***	-0.125***		-0.012***	-0.011***	
	[0.008]	[0.007]		[0.001]	[0.001]	
Spec. Bank × Multiple Specialized Lenders	0.407***	0.047	0.032	0.012**	0.004	0.002
	[0.037]	[0.037]	[0.039]	[0.005]	[0.005]	[0.005]
Constant	5.120***	5.230***	5.178***	0.055***	0.056***	0.049***
	[0.020]	[0.020]	[0.020]	[0.002]	[0.003]	[0.002]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating Category (1-3) FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	353,544	353,537	351,776	353,544	353,537	351,776

Note: In Columns (1)-(3), we regress the loan rate paid by a given firm on the fixed effects specified at the bottom of the table and a dummy denoting whether said firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification. We interact our variable of interest with a dummy that takes the value of 1 if the industry in question is one in which more than one specialized lender operates. In Columns (4)-(6), we use the same specifications as in previous columns, but with "non-performing" indicator as the dependent variable. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

inconsistent with the alternative mechanism of competition among specialized lenders. Finally, the results on loan performance are not as robust as those on interest rates; while the point estimates in Columns (4)-(6) are negative in all our specifications, they are not statistically significant in our most saturated specifications. In Appendix B.7, we show the number of specialized lenders that operate in an industry. We can show that our results are robust to using the exact number of specialized lenders in an industry as an alternative definition of "Multiple Specialized Lenders" in Appendix Table B.8.

5 Extensions and Discussion

This section provides several important model extensions and discussions. We first consider the model extension which endogenizes the bank specialization structure —-that is, Bank A has both general and specialized signals, while Bank B has only general signal, which we have assumed so far. We then show that our theoretical results are robust to a generalized information structure and finally discuss the connection between our model and the industrial organization literature on imperfect competition and adverse selection.

5.1 Information Acquisition and Endogenous Specialization

In this section, we study the lender's information acquisition problem and derive conditions under which the information structure assumed in the baseline model is an equilibrium outcome.

Setting and information acquisition technologies. We extend the baseline model by introducing another borrower firm, b, alongside the original borrower, a. The borrower firms can also be interpreted as two different industries. Two technologies relating to "general" and "specialized" information generate signals. The "general information technology costs κ_g and allows a lender j to process standardized data (e.g., credit reports, income statements) to produce a private general information signal $g_i^j \in \{H, L\}$ for each firm $i \in \{a, b\}$, which are independent conditional on the general fundamental θ_g. This reflects general information collected via standardized and transferable data, such as credit reports and income statements, so once the IT equipment, software, and APIs are installed, credit analysis is easy to implement in multiple firms. The "specialized information technology requires a lender to collect firm-specific data individually. Lender i specializes in firm j by spending κ_s to obtain a private specialized signal s_i^j, distributed according to the CDF $\Phi(s)$ and the PDF $\phi(s)$ for $s \in [0, 1]$. If a bank wants to acquire specialized information about both firms, it needs to pay $2\kappa_s$.

We are interested in the equilibrium in which Bank A only specializes in firm a, Bank B only specializes in firm b and both lenders acquire the general information technology. Given the symmetry of the equilibrium, we omit indexing the specialized signal by the firm i. Note that the baseline model analyzed in Section 3 is the subgame for either firm following the equilibrium information acquisition strategies.

Incentive compatibility conditions. Banks make their information acquisition decisions simultaneously and we assume that information acquisition is observable when banks enter the credit market competition game. Therefore, a lender's deviation from the proposed equilibrium information acquisition will lead to a different information structure in the credit market competition, and we need to derive equilibrium lending profits in all possible subgames following a deviation.

Bank A can deviate in three dimensions: it can choose not to acquire general information, it can choose not to acquire specialized information about firm a, and it can choose to acquire specialized information in firm b. Bank A's incentives to deviate along these dimensions will depend on the costs of acquiring information. As expected, the lower the cost of acquiring general information, the more likely Bank A has incentives to acquire general information and not deviate along this dimension. For deviations along the dimension of specialized information, the cost of acquiring specialized information has to be low enough to make it worth acquiring specialized information in firm a and having an informational advantage over Bank B in this firm, but high enough so that

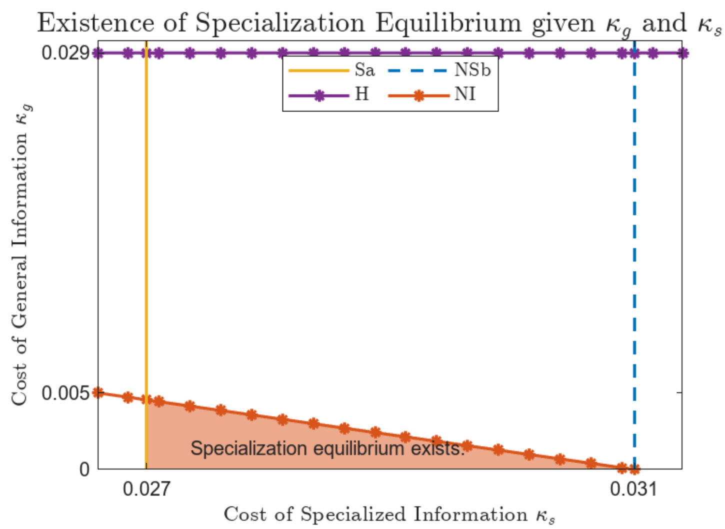

Figure 7: **Specialization Equilibrium.** This figure depicts the incentive compatibility constraints where Bank A does not want to deviate from the specialization equilibrium. Parameters: $\bar{r} = 0.36$, $q_h = 0.8$, $q_s = 0.9$, $\alpha_u = \alpha_d = \alpha = 0.7$, and $\tau = 1$. Note τ captures the signal-to-noise ratio of Bank A's specialized information technology as $s = \mathbb{E}[\theta_s|\theta_s + \epsilon]$ and $\epsilon \sim \mathcal{N}(0, 1/\tau)$.

it is not worth acquiring specialized information in firm b to stop being the least informed lender. This intuition is formally stated in Appendix A.7, where we also characterize the deviation payoffs.

Given this discussion, an equilibrium with lending specialization emerges as long as the benefits of acquiring specialized information to become the more informed lender (e.g., getting s_A^a for Bank A, which is part of the equilibrium strategy in the baseline) are greater than the benefits from acquiring specialized information to stop being the less informed lender (e.g., getting s_A^b for Bank A which deviates from our equilibrium in the baseline). This is confirmed in Figure 7, which depicts the range of information acquisition costs κ_g and κ_s so that the conjectured information structure with a specialized lender and bank competition is indeed an equilibrium.

5.2 General Information Structure

Our multiplicative setting with two independent fundamental states has two features that drive the tractability of our model: the general signal is decisive, and all signals are independent conditional on success. Under these two assumptions, the same solution technique as in Section 3 can be applied to any general information structure. We now discuss these two assumptions, while relegate the detailed characterization of the model with a general information structure in Appendix A.8.

Decisive general signal. In many scenarios, the general information signal is usually used as a prescreening signal and is decisive for loan approval, while the specialized signal collected by the specialized bank tailors interest rate terms (see Section 2.3). To capture this commonly observed lending practice, we assume that lenders are not willing to make a loan offer if the realization of the general signal is low. The multiplicative setting in our baseline model makes the "general" state decisive for project success, making such lending strategies more likely to arise in equilibrium.

Independence conditional on project success. Conditional on project success, all signals — including the specialized one of lender A and the two general ones of both lenders — are independent of each other. Formally,

$$\tilde{g}^A \perp\!\!\!\perp \tilde{g}^B \perp\!\!\!\perp \tilde{s} \,|\, \theta = 1 \,. \tag{30}$$

Because lenders only consider the marginal good type borrower who is payoff relevant, the effects of specialized and general signals on equilibrium strategies are separable if signals are independent conditional on project success. This allows for a closed-form characterizations of the equilibrium.[26]

One can verify that our setting in Section 2.3 with independent general and specialized states satisfies (30), although tractability does not rely on independent general and specialized states. Consider the following example studied by He, Huang, and Parlatore (2024) with $\theta = \theta_1\theta_2\theta_3$, $\theta_g = \theta_1\theta_2$ and $\theta_s = \theta_2\theta_3$. This information structure generalizes (7) in Section 2.3, but still satisfies (30).[27] Since our general information structure allows the general and specialized signal to be correlated, it can be used to study credit market applications such as data sharing and credit registries that induce correlated lender signals.

5.3 Connection to the IO Literature

Our study of the interest rate wedge between asymmetrically informed lenders is related to the industrial organization (IO) literature on imperfect competition and adverse selection (see (Mahoney and Weyl, 2017; Crawford, Pavanini, and Schivardi, 2018)). Within that body of literature, market power (of lenders) and adverse selection (of borrowers) are considered distinct market frictions. Market power refers to the situation where the demand for the firm's (differentiated) products remains relatively inelastic with respect to its price, whereas adverse selection is characterized by the observation that the effective revenue of marginal consumers decreases as the firm raises its price.[28] Combining these two forces, the key takeaway is an interaction effect: while firms with greater market power should charge higher prices, this standard force should be attenuated by adverse selection, which hurts marginal revenue when firms raise their prices.

We highlight two points. First, unlike the IO literature which takes market power and adverse selection as two independent market frictions, our theory takes "information asymmetry" as primitive, with the winner's curse faced by asymmetrically informed lenders as the only underlying economic force. Although one could broadly link the above-mentioned market power and adverse

[26]See Proposition 1 for the baseline model and Proposition 4 in the Appendix for the extension with a general information structure.

[27]The multiplicative structure in (7) is the key: $\theta = 1$ implies that all fundamental states $\{\theta_n, n \in 1, ..., N\}$ take the value of one. Unconditionally, however, the pair-wise correlations of $\{\tilde{g}^A, \tilde{g}^B, s\}$ are all positive, simply because the general state θ_g and specialized state θ_s are correlated.

[28]In the insurance market example used in Mahoney and Weyl (2017), a higher insurance premium is associated with lower quality insurance buyers, and hence a higher service cost. In Crawford, Pavanini, and Schivardi (2018), which studies the enterprise loan market, a higher interest rate may attract worse borrowers or induce riskier projects, leading to lower interest revenues.

selection to unobservable borrower types, they are different conceptually. First, strictly speaking, there is no "market power" enjoyed by the specialized lender in our model; money from any funding source is perfectly fungible just like in Huang (2023). Moreover, there is no "adverse selection" from borrowers either, because both types of borrowers will take loans at any interest rate.[29]

Second, prices in the IO literature mentioned above are "bids" as opposed to "winning bids;", for example, Crawford, Pavanini, and Schivardi (2018) only consider bidding prices. Section 4 has highlighted the importance of distinguishing betweenbids and winning bids in the context of credit market competition with endogenous rejection, and future research should study whether this difference can reverse the conclusions from the IO literature.

6 Concluding Remarks

One of banks' main roles in the economy is producing information to allocate credit. In this paper, we show that the nature of information produced by banks affects the credit market equilibrium and the degree of competition among banks. By considering specialized and general information, we can explain empirical patterns in bank lending specialization—the negative interest rate wedge—that are unexplained by canonical models where information technology is solely characterized by the signal's precision. In a companion paper with a similar credit market competition setting, He, Huang, and Parlatore (2024) distinguishes between the quality (signal precision) and breadth (information span) of information, a distinction that is crucial to understanding the changing landscape in the credit market due to technological advances related to data gathering and processing that lead to the hardening of soft information.

From a modeling perspective, including a continuously distributed signal within a credit market equilibrium enables us to examine private-information-based pricing, a pertinent aspect of significant importance in the banking sector in practice. Furthermore, by incorporating both specialized and general information—which reflect potentially many more underlying states—among asymmetric lenders, our paper markedly advances the field of common-value auction literature involving such asymmetrically informed lenders in which each lender possesses private information (in contrast to Milgrom and Weber (1982) where one bidder knows strictly more than the other). We fully characterize the equilibrium in closed form and anticipate broader applications based on our framework and solution methodology.

[29] To the point of market power, Huang (2023) studies the competition between collateral-backed bank lending (say Citibank) and revenue-based fintech lending (say Square); borrowers view each dollar the same regardless of the lender's identity. To the point of adverse selection, as typical in corporate finance literature (e.g., Tirole, 2010) we are implicitly assuming that both types of borrower receive nonpledgeable private benefits from the project, so they strictly prefer to take the loan even if $r = \bar{r}$.

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A Technical Appendices

A.1 Credit Competition Equilibrium

Proof of Lemma 1

Proof. Note that the property of no gaps implies common support $[\underline{r}, \overline{r}]$. This is because, if a bank's interest rate offering has a larger lower bound or a smaller upper bound interest rate than its competitor's, this is one example of gaps in the first bank's support.

To show that the distributions have no gap, suppose that, say, the support of Bank B's interest rate offering F^B has a gap $(r_1, r_2) \subset [\underline{r}, \overline{r}]$.Then F^A should have no weight in this interval either, as any $r^A(s) \in (r_1, r_2)$ will lead to the same demand for Bank A and so a higher r will be more profitable. It follows that at least one lender, whose competitor's interest rate offering does not have a mass point at r_1 (it is impossible that both distributions have a mass point at r_1), has a profitable deviation by revising r_1 to $r \in (r_1, r_2)$. Contradiction.

Regarding point mass, suppose that one distribution, say F^B has a mass point at $\tilde{r} \in [\underline{r}, \overline{r})$. Then Bank A would not quote any $r^A(s) \in [\tilde{r}, \tilde{r} + \epsilon]$ and it would strictly prefer quoting $r^A = \tilde{r} - \epsilon$ instead. In other words, the support of F^A must have a gap in the interval $[\tilde{r}, \tilde{r} + \epsilon]$. This contradicts the property of no gaps which we have shown. Finally, it is impossible that both distributions have a mass point at $\overline{r}$.

□

Proof of Lemma 2 Before we delve into the details of proof we first explain its logic. Note that s_B^{be} is the highest specialized signal under which Bank A's offer hits $\overline{r}$, given $\pi^B = 0$. Moreover, recall that s_A^{be} is the level of the specialized signal under which Bank A just breaks even when quoting $\overline{r}$. If $s_B^{be} < s_A^{be}$, then we know s hits s_A^{be} (i.e., Bank A hits zero profit) first when s goes down from the top, implying that Bank A will lose money upon at $s = s_B^{be} < s_A^{be}$. Combining these two pieces, we know that quoting $\overline{r}$ at s_B^{be}—which is under the implicit assumption of $\pi^B = 0$—must be off-equilibrium for Bank A. Therefore in equilibrium $\pi^B > 0$ and Bank A withdraws itself upon $s < x = \hat{s} = s_A^{be}$. If on the other hand $s_B^{be} \geq s_A^{be}$, we are in the alternative scenario where $\hat{s} = s_B^{be}$ and $\pi^B = 0$; Bank A who is making a positive profit at s_B^{be} will keep quoting $\overline{r}$ for $s < s_B^{be}$, until $s < x$ upon which it exits.

Proof. First, we argue that equilibrium $\hat{s} \equiv \arg\sup_s \left\{s : r^A(s) \geq \overline{r}\right\}$ either equals s_A^{be} or s_B^{be}. To see this, if $\pi^B = 0$, we have $\hat{s} = s_B^{be}$ by construction. If $\pi^B > 0$, then Bank B always makes an offer upon H, i.e., $F^B(\overline{r}) = 1$. We also know that $F^B\left(\overline{r}^-\right) = 1 - \frac{\int_0^{s^A(r)=\hat{s}^+} t\phi(t)dt}{q_s} < 1$, because Bank A must reject the borrower when s realizes as close to 0 and so $\hat{s} > 0$. Hence, $F^B(r)$ has a point mass at $\overline{r}$. It follows that $F^A(r)$ is open at $\overline{r}$: $\hat{s} = x$ and $\pi^A\left(r^A(\hat{s})\,|\hat{s}\right) = 0$, which is exactly the definition of s_A^{be}, so $\hat{s} = s_A^{be}$ in this case.

Now we prove the claim in this lemma. In the first case of $s_B^{be} < s_A^{be}$, we have $\hat{s} \leq s_A^{be}$ and thus Bank A's probability of winning when quoting $r^A = \overline{r}$ is at most $\frac{\int_0^{s_A^{be}} t\phi(t)dt}{q_s} \geq \frac{\int_0^{\hat{s}} t\phi(t)dt}{q_s} = 1 - F^B\left(\overline{r}^-\right)$. The definition of s_A^{be} says that Bank A upon s_A^{be} breaks even when quoting $r^A\left(s_A^{be}\right) = \overline{r}$ and facing this most favorable winning probability $\frac{\int_0^{s_A^{be}} t\phi(t)dt}{q_s}$. Then upon a worse specialized signal $s_B^{be} < s_A^{be}$, Bank A must reject the borrower because offering $\overline{r}$ leads to losses, which rules out $\hat{s} = s_B^{be}$. According to our earlier observation of $\hat{s} = s_B^{be}$ or s_A^{be}, we have $\hat{s} = s_A^{be}$ and $\pi^B > 0$ in this case, where π^B could be characterized from Eq. (12) at $r = \overline{r}$.

In the second case of $s_B^{be} \geq s_A^{be}$, we have $\hat{s} \leq s_B^{be}$ and thus Bank B's probability of winning when quoting $r^B = \overline{r}$ is at most $\Phi\left(s_B^{be}\right) \geq \Phi(s) = 1 - F^A\left(\overline{r}^-\right)$. The definition of s_B^{be} says that Bank B breaks even when quoting $r^B = \overline{r}$ and facing this most favorable winning probability $\Phi\left(s_B^{be}\right)$. Then if the competition from A were more aggressive, say $1 - F^A\left(\overline{r}^-\right) = \Phi\left(s_A^{be}\right)$, Bank B would make a loss when quoting $\overline{r}$, so $\hat{s} = s_A^{be}$

cannot support an equilibrium. Hence, in this case, $\hat{s} = s_B^{be}$ and $\pi^B = 0$. In addition,

$$\begin{aligned}
0 =& \frac{p_{HH} \int_0^{s_A^{be}} t\phi(t)\, dt}{q_s} \left[\mu_{HH} s_A^{be}(1+\bar{r}) - 1\right] + p_{HL}\left[\mu_{HL} s_A^{be}(1+\bar{r}) - 1\right] \\
=& \frac{p_{HH} \int_0^{s_B^{be}} t\phi(t)\, dt}{q_s} \left[\mu_{HH} x(1+\bar{r}) - 1\right] + p_{HL}\left[\mu_{HL} x(1+\bar{r}) - 1\right] \\
\geq& \frac{p_{HH} \int_0^{s_A^{be}} t\phi(t)\, dt}{q_s} \left[\mu_{HH} x(1+\bar{r}) - 1\right] + p_{HL}\left[\mu_{HL} x(1+\bar{r}) - 1\right],
\end{aligned}$$

where the first equality is the definition of s_A^{be}, the second equality is Bank A's equilibrium break-even condition $0 = \pi^A(\bar{r}|x)$, and the last inequality uses $s_B^{be} \geq s_A^{be}$ in this case. Hence, $x \leq s_A^{be} \leq s_B^{be} = \hat{s}$. ☐

A.2 Proof of Proposition 1

Proof. This part proves that Bank A's equilibrium interest rate quoting strategy as a function of specialized signal $r^A(s)$ is always decreasing; this implies that the FOC that helps us derive Bank A's strategy also ensures the global optimality.

Write Bank A's value $\Pi^A(r,s)$ as a function of its interest rate quote and specialized signal, in the event of $g^A = H$ and s. (We use π to denote the equilibrium profit but Π for any strategy.) Recall that Bank A solves the following problem:

$$\max_r \Pi^A(r,s) = \underbrace{p_{HH}}_{g^A=H, g^B=H} \underbrace{\left[1 - F^B(r)\right]}_{A \text{ wins}} \left[\mu_{HH} s(1+r) - 1\right] + \underbrace{p_{HL}}_{g^A=H, g^B=L} \left[\mu_{HL} s(1+r) - 1\right] \tag{31}$$

with the following FOC:

$$0 = \underbrace{p_{HH}\left[-\frac{dF^B(r)}{dr}\right]}_{\text{lost customer}} \left[\underbrace{\mu_{HH} s(1+r) - 1}_{\text{customer return}}\right] + \underbrace{p_{HH}\left[1 - F^B(r)\right]}_{\text{customer}} \underbrace{\mu_{HH} s}_{\text{MB of customer}} + p_{HL}\mu_{HL} s. \tag{32}$$

One useful observation is that on the support, it must hold that $\mu_{HH} s(1+r) - 1 > 0$; otherwise, $\mu_{HL} s(1+r) - 1 < \mu_{HH} s(1+r) - 1 \leq 0$, implying that Bank A's profit is negative (so it will exit).

Lemma 3. *Consider s_1, s_2 in the interior domain with corresponding interest rate quote r_1 and r_2. The marginal value of quoting r_2 for type $s = s_1$ is*

$$\Pi_r^A(r_2, s_1) = \frac{s_2 - s_1}{\mu_{HH} s_2(1+r_2) - 1}\left\{p_{HH}\left[1 - F^B(r_2)\right]\mu_{HH} + p_{HL}\mu_{HL}\right\}$$

and its sign depends on the sign of $s_2 - s_1$.

Proof. Evaluating the FOC (32) of type s_1 but quoting r_2:

$$\Pi_r^A(r_2, s_1) = p_{HH}\left[-\frac{dF^B(r_2)}{dr}\right]\left[\mu_{HH} s_1(1+r_2) - 1\right] + p_{HH}\left[1 - F^B(r_2)\right]\mu_{HH} s_1 + p_{HL}\mu_{HL} s_1. \tag{33}$$

FOC at type s_2 yields

$$\Pi_r^A(r_2, s_2) = p_{HH}\left[-\frac{dF^B(r_2)}{dr}\right]\left[\mu_{HH} s_2(1+r_2) - 1\right] + p_{HH}\left[1 - F^B(r_2)\right]\mu_{HH} s_2 + p_{HL}\mu_{HL} s_2 = 0,$$

or

$$\frac{dF^B(r_2)}{dr} = \frac{p_{HH}\left[1 - F^B(r_2)\right]\mu_{HH} s_2 + p_{HL}\mu_{HL} s_2}{p_{HH}\left[\mu_{HH} s_2(1+r_2) - 1\right]}. \tag{34}$$

Plugging in this term to (33), $\Pi_r^A(r_2, s_1)$ becomes

$$-\frac{\mu_{HH}s_1(1+r_2)-1}{\mu_{HH}s_2(1+r_2)-1}\left\{p_{HH}\left[1-F^B(r_2)\right]\mu_{HH}s_2+p_{HL}\mu_{HL}s_2\right\}+p_{HH}\left[1-F^B(r_2)\right]\mu_{HH}s_1+p_{HL}\mu_{HL}s_1$$
$$=\left[s_1-\frac{\mu_{HH}s_1(1+r_2)-1}{\mu_{HH}s_2(1+r_2)-1}\cdot s_2\right]\left\{p_{HH}\left[1-F^B(r_2)\right]\mu_{HH}+p_{HL}\mu_{HL}\right\}$$
$$=(s_2-s_1)\cdot\frac{p_{HH}\left[1-F^B(r_2)\right]\mu_{HH}+p_{HL}\mu_{HL}}{\mu_{HH}s_2(1+r_2)-1},$$

which is the claimed marginal benefit of quoting r_2 for type s_1. Its sign depends on $s_2 - s_1$ because the denominator is positive as we noted right after Eq. (32). □

Lemma 3 has three implications. First, as long as $r^A(\cdot)$ is (strictly) increasing in some segment, then Bank A would like to deviate in this segment. To see this, suppose that $r_1 > r_2$ when $s_1 > s_2$ for s_1, s_2 arbitrarily close. Because Lemma 1 has shown that Bank A's strategy is smooth, r_2 is arbitrarily close to r_1. Then $\Pi_r^A(r_2, s_1) < 0$, implying that the value is convex and the Bank A at s_1 (who in equilibrium is supposed to quote r_1) would like to deviate further.

Second, the monotonicity implied by Lemma 3 helps us show that Bank A uses a pure strategy. To see this, for any $\hat{s} \geq s_1 > s_2$ that induce interior quotes $r_1, r_2 \in [\underline{r}, \overline{r})$, however close, in equilibrium we must have $\sup r^A(s_1) < \inf r^A(s_2)$ by monotonicity. Combining this with Part 3 of Lemma 1, i.e., the induced distribution $F^A(\cdot)$ is atomless except for at $\overline{r}$ and has no gaps, we know that Bank A must adopt a pure strategy in the interior of $[\underline{r}, \overline{r})$, or for $s \leq \hat{s}$. Finally, on $s < \hat{s}$ Bank A can quote either $\overline{r}$ or ∞ which generically gives different values; this then rules out randomization.

Third, if $r^A(\cdot)$ is decreasing globally over $\mathcal{S}$, then the FOC is sufficient to ensure global optimality. Consider a type s_1 who would like to deviate to $\check{r} > r_1$; then

$$\Pi^A(\check{r}, s_1) - \Pi^A(r_1, s_1) = \int_{r_1}^{\check{r}} V_r^A(r, s_1)\,dr.$$

Given the monotonicity of $r(s)$, we can find the corresponding type $s(r)$ for $r \in [r_1, \check{r}]$. From Lemma 3 we know that

$$\Pi_r^A(r, s_1) = (s(r) - s_1)\frac{p_{HH}\left[1-F^B(r)\right]\mu_{HH}+p_{HL}\mu_{HL}}{\mu_{HH}s(r)(1+r)-1},$$

which is negative given $s(r) < s_1$. Therefore the deviation gain is negative. Similarly, we can show a negative deviation gain for any $\check{r} < r_1$.

Next, we show that $r^A(\cdot)$ is single-peaked over the space of $[0, 1]$.

Lemma 4. *Given any exogenous $\pi^B \geq 0$, $r^A(\cdot)$ single-peaked over $[0, 1]$ with a maximum point.*

Proof. When $r \in [\underline{r}, \overline{r})$, the derivative of $r^A(s)$ in Eq. (13) with respect to s is

$$\frac{dr^A(s)}{ds} = \frac{p_{HH}\phi(s)\left(\overbrace{p_{HH}\mu_{HH}\left[\int_0^s t\phi(t)\,dt - s\Phi(s)\right]}^{M_1(s)<0,\text{ and }M_1'(s)<0} + \overbrace{p_{LH}\mu_{LH}q_s - \left(\pi^B + p_{LH}\right)\mu_{HH}s}^{M_2(s)?0,\text{ but }M_2'(s)<0}\right)}{\left(p_{HH}\mu_{HH}\int_0^s t\phi(t)\,dt + p_{LH}\mu_{LH}q_s\right)^2}.$$

As $\int_0^s t\phi(t)\,dt < s\Phi(s)$, the first term in the bracket $M_1(s) < 0$, and

$$M_1'(s) = -p_{HH}\mu_{HH}\Phi(s) < 0.$$

For $M_2(s) = p_{LH}\mu_{LH}q_s - \left(\pi^B + p_{LH}\right)\mu_{HH}s$, it has an ambiguous sign, but is decreasing in s. This implies that $M_1(s) + M_2(s)$ decreases with s. It is easy to verify that $M_1(0) + M_2(0) > 0$ and $M_1(1) + M_2(1) < 0$. Therefore $r^A(s)$ first increases and then decreases, i.e. single-peaked. □

Suppose that the peak point is $\tilde{s}$; then Bank A should simply charge $r(s) = \tilde{r}$ for $s < \tilde{s}$ for better profit. This is the standard "ironing" technique and we therefore define the following ironed strategy formally (here, we also take care of the capping $r \leq \overline{r}$):

$$r^A_{ironed}(s) \equiv \sup_{t\in[s,1]} \min\left(r^A(t), \overline{r}\right).$$

By definition $r^A_{ironed}(s)$ is monotonely decreasing.

We now argue that in equilibrium, π^B and $\underline{r}$ adjust so that $r^A(\cdot)$ is always monotonely decreasing over $[x, 1]$. (Since we define $r^A(s) = \infty$ for $s < x$, monotonicity over the entire signal space $[0, 1]$ immediately follows.) There are two subcases to consider.

1. Suppose that $\tilde{r} = \overline{r}$. In this case, $r^A(s)$ in Eq. (13) used in Lemma 3 and 4 does not apply to $s < \tilde{s}$ because the equation is defined only over the left-closed-right-open interval $[\underline{r}, \overline{r})$. Instead, $r^A(s)$ in this region is determined by Bank A's optimality condition: as r^A does not affect the competition from Bank B (which equals $F^B(\overline{r}^-)$), Bank A simply sets the maximum possible rate $r^A(r) = \overline{r}$ unless it becomes unprofitable (for $s < x$). (This is our zero-weak equilibrium with $\pi^B = 0$, and there is no "ironing" in this case.)

2. Suppose that $\tilde{r} < \overline{r}$; then bank A quotes $\tilde{r}$ for all $s < \hat{s}$. But this is not an equilibrium—Bank A now leaves a gap in the interval $[\tilde{r}, \overline{r}]$, contradicting with Lemma 1 (there, we rule out gaps in equilibrium). Intuitively, Bank A is too aggressive, and Bank B always would like to raise its quotes inside $[\tilde{r}, \overline{r}]$ to $\overline{r}$. In equilibrium, π^B and $\underline{r}$ adjust upward, so that the peak point $\tilde{s}$ coincides with $\overline{r}$, resulting in no "ironing" in this case either. (This is our positive-weak equilibrium with $\pi^B > 0$.)

□

A.3 Equilibrium Characterization for Non-Zero Recovery

A.3.1 Specialized lending

In this part, we change our baseline model by assuming that a lender recovers $\delta \in (0, 1)$ from a borrower who defaults. The analysis below shows that non-zero recovery rate is isomorphic to our baseline with zero recovery rate where the lending cost per loan is changed from 1 to $1 - \delta$.

We focus on the primitive conditions under which the general signal is decisive for screening. Specifically, Bank A rejects the borrower upon $g^A = L$, regardless of its specialized signal realization,

$$p_{L\cdot}\left[\mu_{L\cdot}(1+\overline{r}) + (1-\mu_{L\cdot})\delta - 1\right], \Leftrightarrow q_g(1-\alpha_u)\overline{r} < (1-q_g)\alpha_d(1-\delta);$$

in addition, Bank B is only willing to participate when it receives a favorable general signal H,

$$p_{\cdot H}\left[\mu_{\cdot H}(1+\overline{r}) + (1-\mu_{\cdot H})\delta - 1\right] > 0 \Leftrightarrow q_g\alpha_u q_s\overline{r} > \left[q_g(1-q_s)\alpha_u + (1-q_g)(1-\alpha_d)\right](1-\delta).$$

Intuitively, compared with our baseline conditions in Assumption 1, the above conditions change the loss of bad projects from 1 to $1 - \delta$.

Lenders choose interest rate strategies to maximize their profits, which are

$$\begin{aligned}
\pi^A(r|s) &\equiv p_{HH}\left[1-F^B(r)\right]\left[\mu_{HH}s(1+r) + (1-\mu_{HH}s)\delta - 1\right] + p_{HL}\left[\mu_{HL}s(1+r) + (1-\mu_{HL}s)\delta - 1\right] \\
&= p_{HH}\left[1-F^B(r)\right]\left[\mu_{HH}s(1+r-\delta) - (1-\delta)\right] + p_{HL}\left[\mu_{HL}s(1+r-\delta) - (1-\delta)\right] \qquad (35) \\
\pi^B(r) &\equiv p_{HH}\left[1-F^A(r)\right]\mathbb{E}\left[\mu_{HH}\theta_s(1+r-\delta) - (1-\delta)\middle| r \leq r^A(s)\right] + p_{LH}\left[\mu_{LH}q_s(1+r-\delta) - (1-\delta)\right] \\
&= p_{HH}\int_0^{s^A(r)} t\phi(t)\,dt\left[\mu_{HH}s(1-\delta+r) - (1-\delta)\right] + p_{LH}\left[\mu_{LH}q_s(1-\delta+r) - (1-\delta)\right]. \qquad (36)
\end{aligned}$$

The lenders' problems could be nested in our baseline model after replacing lending cost from 1 to $1 - \delta$, so the previous derivation of the equilibrium applies here. We first derive equilibrium strategies as a function of π^B and then characterize π^B in closed form. Bank A's equilibrium strategy $r^A(s)$ over $[\underline{r}, \overline{r})$ makes Bank

B indifferent, and Bank A may offer $\overline{r}$ or ∞ upon worse specialized signals:

$$r^A(s) = \begin{cases} \min\left\{ \frac{\pi^B + (p_{HH}\Phi(s)+p_{LH})(1-\delta)}{p_{HH}\mu_{HH}\int_0^{s^A(r)} t\phi(t)dt + p_{LH}\mu_{LH}q_s} - (1-\delta), \overline{r} \right\}, & \text{for } s \in [x,1], \\ \infty, & \text{for } s \in [0,x), \end{cases}$$

where x satisfies $\pi^A(\overline{r}|x) = 0$ and $\pi^A(r|s)$ is given in Eq. (35). The two lenders' optimality conditions help us pin down Bank B's strategy,

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

Note that Bank A's strategy $r^A(s)$, which makes Bank B indifferent, adjusts for the positive recovery rate δ that affects Bank B's profit. On the other hand, the functional form of $F^B(r)$ is the same as in the baseline and $F^B(r)$ is only affected via the endogenous $r^A(s)$. This is because the key ODE that pins down $F^B(r)$ involves the quality of lenders' existing borrowers but is irrelevant of borrower payoffs.

Last, Bank B's equilibrium profit is

$$\pi^B = \max\left\{ \left[p_{HH}\mu_{HH}\int_0^{s_A^{be}} t\phi(t)\,dt + p_{LH}\mu_{LH}q_s \right](1-\delta+\overline{r}) - \left(p_{HH}\Phi\left(s_A^{be}\right) + p_{LH}\right)(1-\delta), 0 \right\},$$

where s_A^{be} satisfies

$$0 = \pi^A\left(\overline{r}\,\middle|\,s_A^{be}\right) = p_{HH}\frac{\int_0^{s_A^{be}} t\phi(t)\,dt}{q_s} \cdot \left[\mu_{HH}s_A^{be}(1-\delta+\overline{r}) - (1-\delta)\right] + p_{HL}\left[\mu_{HL}s_A^{be}(1-\delta+\overline{r}) - (1-\delta)\right].$$

A.3.2 Canonical models

In this part, we formally characterize the credit competition equilibrium under canonical setting with recovery $\delta \in [0,1)$ from default borrowers. When $\delta = 0$, the bad news signal case corresponds to He, Huang, and Zhou (2023) and the symmetric signal structure case corresponds to Broecker (1990); Hauswald and Marquez (2003); the analysis in Appendix A.4 rely on this equilibrium characterization under $\delta = 0$.

First, we characterize lender strategies $F^j(r)$ for $j \in \{A, B\}$ as functions of primitives $p_{g^A g^B}$, $\mu_{g^A g^B}$ and endogenous variables $\pi^A, \pi^B, \underline{r}$. These functions apply to both bad news and symmetric signal structure. Then we characterize $p_{g^A g^B}$, $\mu_{g^A g^B}$ and endogenous variables $\pi^A, \pi^B, \underline{r}$ for the two signal structures separately.

We focus on the primitive conditions under which a lender rejects the borrower upon $g^j = L$ for $j \in \{A, B\}$, and they are later separately characterized for both bad news signal structure and symmetric structures. Upon $g^j = H$, lenders' profits are

$$\begin{aligned} \pi^A(r) =& p_{HH}\left[1 - F^B(r)\right]\left[\mu_{HH}(1+r) + (1-\mu_{HH})\delta - 1\right] + p_{HL}\left[\mu_{HL}(1+r) + (1-\mu_{HL})\delta - 1\right], \\ \pi^B(r) =& p_{HH}\left[1 - F^A(r)\right]\left[\mu_{HH}(1+r) + (1-\mu_{HH})\delta - 1\right] + p_{LH}\left[\mu_{LH}(1+r) + (1-\mu_{LH})\delta - 1\right]. \end{aligned}$$

Since both lenders use mixed strategies, they earn a constant profit π^j which we take as given for now. Therefore, a lender's strategy $F^j(r)$ could be solved from its competitor indifference condition over common support $[\underline{r}, \overline{r}]$:

$$F^A(r) = \begin{cases} 1 - \frac{\pi^B - p_{LH}[\mu_{LH}(r+1-\delta) - (1-\delta)]}{p_{HH}(\mu_{HH}(r+1-\delta) - (1-\delta))}, & \text{for } r \in [\underline{r}, \overline{r}), \\ 1, & \text{for } r = \overline{r}, \end{cases} \tag{37}$$

$$F^B(r) = 1 - \frac{\pi^A - p_{HL}\left[\mu_{HL}(r+1-\delta) - (1-\delta)\right]}{p_{HH}\left(\mu_{HH}(r+1-\delta) - (1-\delta)\right)}, \quad \text{for } r \in [\underline{r}, \overline{r}]. \tag{38}$$

Since Bank A with superior information technology must make a higher profit than Bank B, we have $\pi^A > 0$ and $F^A(\bar{r}) = 1$ while whether $F^B(\bar{r}) = 1$ depends on the endogenous profit π^B.

Bad-news signal structure In the bad news signal structure, $\mathbb{P}(g^j = H|\theta = 1) = 1$ for $j \in \{A, B\}$. Under this structure, a lender always rejects a borrower upon L because it reveals the borrower to be bad type and the loan has negative NPV (recovery $\delta < 1$).

The signal probabilities $p_{g^A g^B}$ and posterior upon signals $\mu_{g^A g^B}$ in Eq. (37) and (38) are

$$\begin{aligned} p_{HH} &= q + (1-q)\left(1-\alpha^A\right)\left(1-\alpha^B\right), \quad \mu_{HH} = \frac{q}{p_{HH}}, \\ p_{HL} &= (1-q)\left(1-\alpha^A\right)\alpha^B, \quad \mu_{HL} = 0, \\ p_{LH} &= (1-q)\,\alpha^A\left(1-\alpha^B\right), \quad \mu_{LH} = 0. \end{aligned}$$

The remaining equilibrium variables are

$$\begin{aligned} \pi^B &= 0, \\ \underline{r} &= \frac{(1-q)\left(1-\alpha^B\right)(1-\delta)}{q}, \\ \pi^A &= q\underline{r} - (1-q)\left(1-\alpha^A\right)(1-\delta). \end{aligned}$$

Symmetric signal structure In the symmetric signal structure, lender j's signal correctly identifies the project quality with precision α^j, i.e., $\mathbb{P}(g^j = H|\theta = 1) = \mathbb{P}(g^j = L|\theta = 0) = \alpha^j$ for $j \in \{A, B\}$. We focus on the primitive condition under which a lender always rejects a borrower upon L. Because Bank A with a higher precision $\alpha^A > \alpha^B$ has a worse posterior upon L than Bank B, it is sufficient to require the condition for Bank B,

$$p_{\cdot L}[\mu_{\cdot L}(1-\delta+\bar{r}) + (1-\mu_{\cdot L}\delta - 1] < 0 \Leftrightarrow q(1-\alpha^B)\bar{r} < (1-q)\alpha^B(1-\delta).$$

The signal probabilities $p_{g^A g^B}$ and posteriors $\mu_{g^A g^B}$ in Eq. (37) and (38) are

$$\begin{aligned} p_{HH} &= q\alpha^A\alpha^B + (1-q)\left(1-\alpha^A\right)\left(1-q^B\right), \quad \mu_{HH} = \frac{q\alpha^A\alpha^B}{p_{HH}}, \\ p_{HL} &= q\alpha^A\left(1-\alpha^B\right) + (1-q)\left(1-\alpha^A\right)q^B, \quad \mu_{HL} = \frac{q\alpha^A\left(1-\alpha^B\right)}{p_{HL}}, \\ p_{LH} &= q\left(1-\alpha^A\right)\alpha^B + (1-q)\,\alpha^A\left(1-q^B\right), \quad \mu_{LH} = \frac{q\left(1-\alpha^A\right)\alpha^B}{p_{LH}}. \end{aligned}$$

The other equilibrium variables $\pi^A, \pi^B, \underline{r}$ depend on whether the equilibrium is zero weak or positive weak. When

$$p_{LH}\left[\mu_{LH}\left(\bar{r}+1-\delta\right) - (1-\delta)\right] \le 0,$$

the equilibrium is zero weak and

$$\begin{aligned} \pi^B &= 0, \\ \underline{r} &= \frac{(1-q)\left(1-\alpha^B\right)(1-\delta)}{q\alpha^B}, \\ \pi^A &= q\alpha^A\underline{r} - (1-q)\left(1-\alpha^A\right)(1-\delta). \end{aligned}$$

Otherwise, the equilibrium is positive weak and

$$\begin{aligned}F^B(\bar{r}) = 1 \Rightarrow \pi^A &= p_{HL}\left[\mu_{HL}(\bar{r}+1-\delta)-(1-\delta)\right],\\ \underline{r} &= \frac{\pi^A+(1-q)\left(1-\alpha^A\right)(1-\delta)}{q\alpha^A},\\ \pi^B &= q\alpha^B\underline{r}-(1-q)\left(1-\alpha^B\right)(1-\delta).\end{aligned}$$

A.4 Proof of Proposition 2

This part studies canonical models where each lender has a (general) binary signal g^j for $j \in \{A, B\}$,

$$\mathbb{P}(g^j = H|\theta = 1) = \alpha_u^j, \quad \mathbb{P}(g^j = L|\theta = 0) = \alpha_d^j.$$

$F^j(r)$ with $j \in \{A, B\}$ indicates the distribution of lender j's interest rate offering.

Lemma 5. *For any $r \in [\underline{r}, \bar{r})$, we have*

$$\frac{F^B(r)}{F^A(r)} = \frac{\alpha_u^A}{\alpha_u^B}, \; \frac{dF^B(r)/dr}{dF^A(r)/dr} = \frac{\alpha_u^A}{\alpha_u^B}.$$

Proof. For any $r \in [\underline{r}, \bar{r})$, lenders' profit functions are

$$\pi^A = \underbrace{p_{HH}}_{g^B=H}\underbrace{\left(1-F^B(r)\right)}_{A\text{ wins}}\left[\mu_{HH}(r+1)-1\right] + \underbrace{p_{HL}}_{g^B=L}\left[\mu_{HL}(r+1)-1\right], \tag{39}$$

$$\pi^B = \underbrace{p_{HH}}_{g^A=H}\underbrace{\left(1-F^A(r)\right)}_{B\text{ wins}}\left[\mu_{HH}(r+1)-1\right] + \underbrace{p_{LH}}_{g^A=L}\left[\mu_{LH}(r+1)-1\right]. \tag{40}$$

These two equations imply that

$$\frac{F^B(r)}{F^A(r)} = \frac{p_{HH}\left[\mu_{HH}(r+1)-1\right]+p_{HL}\left[\mu_{HL}(r+1)-1\right]-\pi^A}{p_{HH}\left[\mu_{HH}(r+1)-1\right]+p_{LH}\left[\mu_{LH}(r+1)-1\right]-\pi^B}. \tag{41}$$

And, evaluating Eq. (39), (40) at $r = \underline{r}$ and using $F^A(\underline{r}) = F^B(\underline{r}) = 1$ gives lenders' profits:

$$\begin{aligned}\pi^A(\underline{r}) &= p_{HH}\left[\mu_{HH}(\underline{r}+1)-1\right]+p_{HL}\left[\mu_{HL}(\underline{r}+1)-1\right],\\ \pi^B(\underline{r}) &= p_{HH}\left[\mu_{HH}(\underline{r}+1)-1\right]+p_{LH}\left[\mu_{LH}(\underline{r}+1)-1\right].\end{aligned}$$

Using these in Eq. (41), we have

$$\frac{F^B(r)}{F^A(r)} = \frac{(p_{HH}\mu_{HH}+p_{HL}\mu_{HL})(r-\underline{r})}{(p_{HH}\mu_{HH}+p_{LH}\mu_{LH})(r-\underline{r})} = \frac{\mathbb{P}\left(g^A=H,\theta=1\right)}{\mathbb{P}\left(g^B=H,\theta=1\right)} = \frac{\alpha_u^A}{\alpha_u^B}.$$

Here, $F^B(r) = \frac{\alpha_u^A}{\alpha_u^B}F^A(r)$ immediately implies that $\frac{dF^B(r)/dr}{dF^A(r)/dr} = \frac{\alpha_u^A}{\alpha_u^B}$. □

Proof of Proposition 2

Part 1: Bad-news signal structure. This structure corresponds to

$$\alpha_u^A = \alpha_u^B = 1, \quad 1 > \alpha_d^A > \alpha_d^B > 0;$$

i.e., lenders only make Type II mistakes. In this part, we use $\alpha^j \equiv \alpha_d^j$ as a lender's signal precision, which captures the probability that bad-type borrowers are correctly identified as L, and $\alpha^A > \alpha^B$.

Proof. From Lemma 5, lender bidding strategies $F^A(\cdot), F^B(\cdot)$ over $[0,\overline{r}] \cup \{\infty\}$ satisfy

$$F^B(r) = \begin{cases} F^A(r), & r \in [0, \overline{r}), \\ F^A(r^-), & r = \overline{r}. \end{cases}$$

We use this result to express Δr as a function of $F^B(r)$. Specifically,

$$\begin{aligned}
\mathbb{E}\left[r^A \middle| r^A < r^B \le \infty\right] &= \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] r dF^A(r) + p_{HL}\int_{\underline{r}}^{\overline{r}} r dF^A(r)}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] dF^A(r) + p_{HL}} \\
&= \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] r dF^B(r) + p_{HH}\overline{r}\left[1-F^B(\overline{r})\right]^2 + p_{HL}\left[\overline{r} - \int_{\underline{r}}^{\overline{r}} F^B(r)\,dr\right]}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] dF^B(r) + p_{HH}\left[1-F^B(\overline{r})\right]^2 + p_{HL}} \\
&= \overline{r} - \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left\{\frac{1}{2} - \frac{\left[1-F^B(r)\right]^2}{2}\right\} dr + p_{HL}\int_{\underline{r}}^{\overline{r}} F^B(r)\,dr}{p_{HH}\left\{-\frac{\left[1-F^B(\overline{r})\right]^2}{2} + \frac{1}{2}\right\} + p_{HH}\left[1-F^B(\overline{r})\right]^2 + p_{HL}},
\end{aligned}$$

and

$$\begin{aligned}
\mathbb{E}\left[r^B \middle| r^B < r^A \le \infty\right] &= \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^A(r)\right] r dF^B(r) + p_{LH}\int_{\underline{r}}^{\overline{r}} r dF^B(r)}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] dF^B(r) + p_{LH}F^B(\overline{r})} \\
&= \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] r dF^B(r) + p_{LH}\left[\overline{r}F^B(\overline{r}) - \int_{\underline{r}}^{\overline{r}} F^B(r)\,dr\right]}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right] dF^B(r) + p_{LH}F^B(\overline{r})} \\
&= \overline{r} - \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left\{\frac{1}{2} - \frac{\left[1-F^B(r)\right]^2}{2}\right\} dr + p_{LH}\int_{\underline{r}}^{\overline{r}} F^B(r)\,dr}{p_{HH}\left\{\frac{1}{2} - \frac{\left[1-F^B(\overline{r})\right]^2}{2}\right\} + p_{LH}F^B(\overline{r})}.
\end{aligned}$$

Hence,

$$\begin{aligned}
&\Delta r \equiv \mathbb{E}\left[r^A \middle| r^A < r^B \le \infty\right] - \mathbb{E}\left[r^B \middle| r^B < r^A \le \infty\right] \\
&= \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left\{\frac{1}{2} - \frac{\left[1-F^B(r)\right]^2}{2}\right\} dr + p_{LH}\int_{\underline{r}}^{\overline{r}} F^B(r)\,dr}{p_{HH}\left\{\frac{1}{2} - \frac{\left[1-F^B(\overline{r})\right]^2}{2}\right\} + p_{LH}F^B(\overline{r})} - \frac{p_{HH}\int_{\underline{r}}^{\overline{r}}\left\{\frac{1}{2} - \frac{\left[1-F^B(r)\right]^2}{2}\right\} dr + p_{HL}\int_{\underline{r}}^{\overline{r}} F^B(r)\,dr}{p_{HH}\left\{-\frac{\left[1-F^B(\overline{r})\right]^2}{2} + \frac{1}{2}\right\} + p_{HH}\left[1-F^B(\overline{r})\right]^2 + p_{HL}}.
\end{aligned} \tag{42}$$

Now we plug in the expressions of $F^B(r)$ to show that the canonical model leads to counterfactual predictions when $\overline{r}$ is relatively small. From He, Huang, and Zhou (2023),

$$F^B(r) = \frac{r - \underline{r}}{r - \underline{r}\left(1-\alpha^A\right)},$$

and the key terms are accordingly

$$\int_{\underline{r}}^{\overline{r}} F^B(r)\,dr = \overline{r} - \underline{r} - \alpha^A \underline{r}\ln\left(\frac{\overline{r}}{\underline{r}} - 1 + \alpha^A\right) + \alpha^A \underline{r}\ln\alpha^A,$$

$$\int_{\underline{r}}^{\overline{r}}\left\{\frac{1}{2} - \frac{\left[1-F^B(r)\right]^2}{2}\right\} dr = \frac{\underline{r}}{2}\cdot\frac{\left(\frac{\overline{r}}{\underline{r}} - 1\right)^2}{\frac{\overline{r}}{\underline{r}} - 1 + \alpha^A}.$$

Let $M(\overline{r}) \equiv \frac{\overline{r}}{\underline{r}} - \left(1-\alpha^A\right)$. Multiply Δr by both denominators in Eq. (42) (which are positive as the probability of lending), and one can show that

$$\Delta r \propto p_{HH}\cdot\frac{\underline{r}\alpha^A}{2}\cdot\left(\frac{M-\alpha^A}{M}\right)^2\left(\frac{p_{HH}\alpha^A}{M}+p_{LH}\right)+\frac{p_{HH}}{2}\left[\int_{\underline{r}}^{\overline{r}}F^B(r)\right](p_{LH}+p_{HL})\left(\frac{\alpha^A}{M}\right)^2$$
$$+p_{LH}p_{HL}\frac{\alpha^A}{M}\left[\int_{\underline{r}}^{\overline{r}}F^B(r)\right]+(p_{HL}-p_{LH})\frac{p_{HH}}{2}\cdot\underline{r}\cdot\frac{\left(M-\alpha^A\right)^2}{M}-(p_{HL}-p_{LH})\frac{p_{HH}}{2}\left[\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr\right].$$

Note that only the last term $-(p_{HL}-p_{LH})\frac{p_{HH}}{2}\left[\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr\right]$ is negative. In addition, this term approaches zero as $\overline{r}\to\underline{r}=\frac{(1-q)\left(1-\alpha^B\right)}{q}$, and

$$\frac{\partial\left[\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr\right]}{\partial\overline{r}}=1-\frac{\alpha^A}{M}>0.$$

Therefore, there exists some threshold $\hat{\overline{r}}$ such that when $\overline{r}\le\hat{\overline{r}}$, the canonical model has counterfactual prediction $\Delta r>0$. □

Part 2: Symmetric signal structure. This structure corresponds to

$$\alpha^j\equiv\alpha_u^j=\alpha_d^j\in\left(\frac{1}{2},1\right],\quad\text{for}\quad j\in\{A,B\}.$$

In this context, the specialized lender Bank A's signal is more precise, $\alpha^A>\alpha^B$.

Lemma 6. $\mathbb{E}\left[r^A\middle|r^A<r^B\le\infty\right]\ge\mathbb{E}\left[r^B\middle|r^B<r^A\le\infty\right]$ *is equivalent to the following inequality*

$$\frac{\mathbb{P}\left(g^A=H\right)\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr+p_{HH}\int_{\underline{r}}^{\overline{r}}F^A(r)\,rdF^B(r)-p_{HH}\overline{r}\frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2}{p_{HH}\left[1-F^B(\overline{r})+\frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right]+p_{HL}}$$
$$\le\frac{\mathbb{P}\left(g^B=H\right)\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr+p_{HH}\int_{\underline{r}}^{\overline{r}}F^A(r)\,rdF^B(r)-p_{HH}\frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\overline{r}}{p_{HH}\left[F^B(\overline{r})-\frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right]+p_{LH}F^B(\overline{r})}.$$

Proof. The expected rate of a lender's loan is

$$\mathbb{E}\left[r^A\middle|r^A<r^B\le\infty\right]\triangleq\frac{\underbrace{p_{HH}}_{\text{B gets H}}\int_{\underline{r}}^{\overline{r}}\underbrace{\left[1-F^B(r)\right]}_{\text{A wins}}rdF^A(r)+\underbrace{p_{HL}}_{\text{B gets L}}\int_{\underline{r}}^{\overline{r}}rdF^A(r)}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^B(r)\right]dF^A(r)+p_{HL}},\tag{43}$$

$$\mathbb{E}\left[r^B\middle|r^B<r^A\le\infty\right]\triangleq\frac{\underbrace{p_{HH}}_{\text{A gets H}}\int_{\underline{r}}^{\overline{r}}\underbrace{\left[1-F^A(r)\right]}_{\text{B wins}}rdF^B(r)+\underbrace{p_{LH}}_{\text{A gets L}}\int_{\underline{r}}^{\overline{r}}rdF^B(r)}{p_{HH}\int_{\underline{r}}^{\overline{r}}\left[1-F^A(r)\right]dF^B(r)+p_{LH}F^B(\overline{r})}.\tag{44}$$

In the first step, we rewrite the equations as functions of $dF^B(r)$ and dr which are continuous at $\overline{r}$. Using integration by parts and Lemma 5, we have

$$\int_{\underline{r}}^{\overline{r}}rdF^A(r)=rF^A(r)\Big|_{\underline{r}}^{\overline{r}}-\int_{\underline{r}}^{\overline{r}}F^A(r)\,dr=\overline{r}-\int_{\underline{r}}^{\overline{r}}F^A(r)\,dr=\overline{r}-\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr.$$

In the last step, although Lemma 5 does not apply at $r=\overline{r}$, it is of zero measure. Similarly, the probability of Bank A winning in competition is

$$\int_{\underline{r}}^{\overline{r}} \left[1 - F^B(r)\right] dF^A(r) = \int_{\underline{r}}^{\overline{r}} dF^A(r) - \int_{\underline{r}}^{\overline{r}} F^B(r)\, dF^A(r)$$

$$\underbrace{=}_{\text{integration by parts}} 1 - \left[F^B(\overline{r}) - \int_{\underline{r}}^{\overline{r}} F^A(r)\, dF^B(r)\right]$$

$$\underbrace{=}_{F^A = \frac{\alpha^B}{\alpha^A} F^B} 1 - F^B(\overline{r}) + \int_{\underline{r}}^{\overline{r}} \frac{\alpha^B}{\alpha^A} F^B(r)\, dF^B(r)$$

$$= 1 - F^B(\overline{r}) + \frac{\alpha^B}{2\alpha^A} \left(F^B(\overline{r})\right)^2,$$

and thus the probability of Bank B winning is the residual

$$\int_{\underline{r}}^{\overline{r}} \left[1 - F^A(r)\right] dF^B(r) = F^B(\overline{r}) - \frac{\alpha^B}{2\alpha^A} \left(F^B(\overline{r})\right)^2.$$

Similarly,

$$\int_{\underline{r}}^{\overline{r}} F^B(r)\, r dF^A(r) = \int_{\underline{r}}^{\overline{r}-} F^B(r)\, r dF^A(r) + F^B(\overline{r})\, \overline{r} \left[1 - F^A\left(\overline{r}^-\right)\right]$$

$$\underbrace{=}_{F^A = \frac{\alpha^B}{\alpha^A} F^B,\, F^B\left(\overline{r}^-\right) = F^B(\overline{r})} \int_{\underline{r}}^{\overline{r}} F^A(r)\, r dF^B(r) + F^B(\overline{r})\, \overline{r} \left(1 - \frac{\alpha^B}{\alpha^A} F^B(\overline{r})\right)$$

Plug these terms into Eq. (43) and (44), and we have

$$\mathbb{E}\left[r^A \middle| r^A < r^B \leq \infty\right] = \frac{\mathbb{P}\left(g^A = H\right) \int_{\underline{r}}^{\overline{r}} r dF^A(r) - p_{HH} \int_{\underline{r}}^{\overline{r}} F^B(r)\, r dF^A(r)}{p_{HH}\left[1 - F^B(\overline{r}) + \frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right] + p_{HL}}$$

$$= \overline{r} - \frac{\mathbb{P}\left(g^A = H\right) \frac{\alpha^B}{\alpha^A} \int_{\underline{r}}^{\overline{r}} F^B(r)\, dr + p_{HH} \int_{\underline{r}}^{\overline{r}} F^A(r)\, r dF^B(r) - p_{HH} \overline{r} \frac{\alpha^B}{2\alpha^A} \left(F^B(\overline{r})\right)^2}{p_{HH}\left[1 - F^B(\overline{r}) + \frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right] + p_{HL}};$$

for Bank B,

$$\mathbb{E}\left[r^B \middle| r^B < r^A \leq \infty\right] = \frac{\mathbb{P}\left(g^B = H\right) \int_{\underline{r}}^{\overline{r}} r dF^B(r) - p_{HH} \int_{\underline{r}}^{\overline{r}} F^A(r)\, r dF^B(r)}{p_{HH}\left[F^B(\overline{r}) - \frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right] + p_{LH} F^B(\overline{r})}$$

$$= \overline{r} - \frac{\mathbb{P}\left(g^B = H\right) \int_{\underline{r}}^{\overline{r}} F^B(r)\, dr + p_{HH} \int_{\underline{r}}^{\overline{r}} F^A(r)\, r dF^B(r) - p_{HH} \frac{\alpha^B}{2\alpha^A} \left(F^B(\overline{r})\right)^2 \overline{r}}{p_{HH}\left[F^B(\overline{r}) - \frac{\alpha^B}{2\alpha^A}\left(F^B(\overline{r})\right)^2\right] + p_{LH} F^B(\overline{r})}.$$

Therefore, $\mathbb{E}\left[r^A \middle| r^A < r^B \leq \infty\right] \geq \mathbb{E}\left[r^B \middle| r^B < r^A \leq \infty\right]$ is equivalent to the stated inequality. □

Lemma 7. *In the case of* $q > \frac{1}{1+\overline{r}}$*, when* $\alpha^B \uparrow \alpha^A$*, there exists a threshold* $\hat{\alpha}\left(\alpha^A\right) < \alpha^A$ *so that when* $\alpha^B > \hat{\alpha}\left(\alpha^A\right)$ *we have* $F^B(\overline{r}) = 1$*.*

Proof. Let $\alpha^B = \alpha^A - \epsilon$. Bank B's profit could be pinned down by setting $r = \overline{r}^-$,

$$\begin{aligned}\pi^B =& p_{HH}\left[1 - F^A\left(\overline{r}^-\right)\right]\left[\mu_{HH}\left(\overline{r}+1\right)-1\right] + p_{LH}\left[\mu_{LH}\left(\overline{r}+1\right)-1\right] \\ \underbrace{\geq}_{F^A\left(\overline{r}^-\right)\leq 1} & \; p_{LH}\left(\mu_{LH}\left(\overline{r}+1\right)-1\right) \\ \underbrace{=}_{\alpha^B=\alpha^A-\epsilon} & \; q\left(1-\alpha^A\right)\left(\alpha^A-\epsilon\right)\overline{r} - (1-q)\,\alpha^A\left(1-\left(\alpha^A-\epsilon\right)\right) \\ =& \left(1-\alpha^A\right)\alpha^A\left[q\overline{r}-(1-q)\right] - \epsilon\left[q\left(1-\alpha^A\right)\overline{r} + (1-q)\,\alpha^A\right].\end{aligned}$$

Hence, when $\epsilon < \frac{\left(1-\alpha^A\right)\alpha^A\left[q\overline{r}-(1-q)\right]}{q\left(1-\alpha^A\right)\overline{r}+(1-q)\alpha^A}$, or equivalently, when

$$\alpha^B > \hat{\alpha}\left(\alpha^A\right) = \alpha^A - \frac{\left(1-\alpha^A\right)\alpha^A\left[q\overline{r}-(1-q)\right]}{q\left(1-\alpha^A\right)\overline{r}+(1-q)\,\alpha^A},$$

we have $\pi^B > 0$ and $F^B\left(\overline{r}\right) = 1$. □

Now we prove the part 2 of Proposition 2. There are two cases depending on whether $q < \frac{1}{1+\overline{r}}$, i.e., whether the project has a negative NPV at prior.

The first case of $q < \frac{1}{1+\overline{r}}$ is easier. When $\alpha^B \uparrow \alpha^A$ and $\alpha^A - \alpha^B = o\left(q - \frac{1}{1+\overline{r}}\right)$, Bank B's signal distributions and strategies approach that of Bank A except at $r = \overline{r}$ (Lemma 5):

$$F^B\left(r\right) \uparrow F^A\left(r\right) \quad \text{for any} \quad r \in \left[\underline{r}, \overline{r}\right), \quad \text{and} \quad F^B\left(\overline{r}\right) < 1 = F^A\left(\overline{r}\right).$$

Then from the expressions of $\mathbb{E}\left[r^A\middle| r^A < r^B \leq \infty\right]$ and $\mathbb{E}\left[r^B\middle| r^B < r^A \leq \infty\right]$ in Lemma 6,

$$\begin{aligned}\frac{\overline{r} - \mathbb{E}\left[r^A\middle| r^A < r^B \leq \infty\right]}{\overline{r} - \mathbb{E}\left[r^B\middle| r^B < r^A \leq \infty\right]} =& \frac{p_{HH}\left[F^B\left(\overline{r}\right) - \frac{1}{2}\left(F^B\left(\overline{r}\right)\right)^2\right] + p_{LH}F^B\left(\overline{r}\right)}{p_{HH}\left[1 - F^B\left(\overline{r}\right) + \frac{1}{2}\left(F^B\left(\overline{r}\right)\right)^2\right] + p_{HL}} \\ \underbrace{\leq}_{\text{RHS set } F^B\left(\overline{r}\right)=1} & \frac{\frac{1}{2}p_{HH} + p_{LH}}{\frac{1}{2}p_{HH} + p_{HL}} = 1,\end{aligned} \tag{45}$$

where the last inequality holds because the ratio is increasing in $F^B\left(\overline{r}\right)$. ($F^B\left(\overline{r}\right) - \frac{1}{2}\left(F^B(\overline{r})\right)^2$ in both the numerator and denominator is monotone increasing when $F^B(\overline{r}) \in (0,1]$.) Hence, $\mathbb{E}\left[r^A\middle| r^A < r^B \leq \infty\right] \geq \mathbb{E}\left[r^B\middle| r^B < r^A \leq \infty\right]$ always holds in this case.

Now consider the second case $q \geq \frac{1}{1+\overline{r}}$. When $\alpha^B \to \alpha^A$, since $\mathbb{E}\left[r^A\middle| r^A < r^B \leq \infty\right]$ decreases while $\mathbb{E}\left[r^B\middle| r^B < r^A \leq \infty\right]$ increases in $F^B\left(\overline{r}\right)$, it is sufficient to show that the equivalent inequality in Lemma 6 holds under $F^B\left(\overline{r}\right) = 1$, i.e.,

$$\begin{aligned}& \frac{\mathbb{P}\left(g^A = H\right)\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}} F^B\left(r\right)dr + p_{HH}\int_{\underline{r}}^{\overline{r}} F^A\left(r\right)r dF^B\left(r\right) - p_{HH}\overline{r}\frac{\alpha^B}{2\alpha^A}}{p_{HH}\frac{\alpha^B}{2\alpha^A} + p_{HL}} \\ \leq & \frac{\mathbb{P}\left(g^B = H\right)\int_{\underline{r}}^{\overline{r}} F^B\left(r\right)dr + p_{HH}\int_{\underline{r}}^{\overline{r}} F^A\left(r\right)r dF^B\left(r\right) - p_{HH}\frac{\alpha^B}{2\alpha^A}\overline{r}}{p_{HH}\left(1 - \frac{\alpha^B}{2\alpha^A}\right) + p_{LH}},\end{aligned} \tag{46}$$

where both the LHS and RHS are positive. When $q > \frac{1}{1+\overline{r}}$, recall that Lemma 7 shows $F^B\left(\overline{r}\right) = 1$ as $\alpha^B \to \alpha^A$ under $q > \frac{1}{1+\overline{r}}$ and so the inequality is also necessary.

Denote by $N \triangleq \int_{\underline{r}}^{\overline{r}} F^B(r)\,dr > 0$, and $M \triangleq \overline{r}\frac{\alpha^B}{2\alpha^A} - \int_{\underline{r}}^{\overline{r}} F^A(r)\,rdF^B(r)$. $M > 0$ because

$$\int_{\underline{r}}^{\overline{r}} F^A(r)\,rdF^B(r) < \overline{r}\int_{\underline{r}}^{\overline{r}} F^A(r)\,dF^B(r) = \overline{r}\int_{\underline{r}}^{\overline{r}} \frac{\alpha^B}{\alpha^A}F^B(r)\,dF^B(r) = \overline{r}\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}} d\left(\frac{F^B(r)^2}{2}\right) = \overline{r}\frac{\alpha^B}{2\alpha^A}.$$

Collect terms in the key inequality (46), we have

$$\begin{aligned}&\left\{\left[p_{HH}\left(1-\frac{\alpha^B}{2\alpha^A}\right)+p_{LH}\right](p_{HH}+p_{HL})\frac{\alpha^B}{\alpha^A}-\left(p_{HH}\frac{\alpha^B}{2\alpha^A}+p_{HL}\right)(p_{HH}+p_{LH})\right\}N\\ \le & p_{HH}\left[p_{HH}\left(1-\frac{\alpha^B}{2\alpha^A}\right)+p_{LH}-\left(p_{HH}\frac{\alpha^B}{2\alpha^A}+p_{HL}\right)\right]M \qquad (47)\end{aligned}$$

Let $\alpha^B = \alpha^A - \epsilon$ and calculate the coefficients. Note that as $\alpha^B = \alpha^A - \epsilon$, we have $p_{HL} - p_{LH} = (2q-1)\,\epsilon$.[30] The coefficient on the LHS of (47):

$$\begin{aligned}&\left[p_{HH}\left(1-\frac{\alpha^B}{2\alpha^A}\right)+p_{LH}\right](p_{HH}+p_{HL})\frac{\alpha^B}{\alpha^A}-\left(p_{HH}\frac{\alpha^B}{2\alpha^A}+p_{HL}\right)(p_{HH}+p_{LH})\\ =&\left(\frac{p_{HH}}{2}+\frac{\epsilon}{2\alpha^A}p_{HH}+p_{LH}\right)(p_{HH}+p_{HL})\left(1-\frac{\epsilon}{\alpha^A}\right)-\left(\frac{p_{HH}}{2}-\frac{\epsilon}{2\alpha^A}p_{HH}+p_{HL}\right)(p_{HH}+p_{LH})\\ =&-\frac{p_{HH}}{2}(2q-1)\,\epsilon+\frac{\epsilon}{2\alpha^A}p_{HH}^2-\frac{\epsilon}{2\alpha^A}p_{LH}p_{HH}-\frac{\epsilon}{\alpha^A}p_{LH}p_{HL}\end{aligned}$$

The coefficient on the RHS of (47):

$$\begin{aligned}p_{HH}\left[p_{HH}\left(1-\frac{\alpha^B}{2\alpha^A}\right)+p_{LH}-\left(p_{HH}\frac{\alpha^B}{2\alpha^A}+p_{HL}\right)\right]&=\frac{\epsilon}{\alpha^A}p_{HH}^2-p_{HH}(p_{HL}-p_{LH})\\ &=\frac{\epsilon}{\alpha^A}p_{HH}^2-p_{HH}(2q-1)\,\epsilon.\end{aligned}$$

Plug the coefficients back into the inequality (47), so we need to show that

$$\begin{aligned}0\le&\left\{\frac{\epsilon}{\alpha^A}p_{HH}^2-p_{HH}(2q-1)\,\epsilon\right\}M-\left\{-\frac{p_{HH}}{2}(2q-1)\,\epsilon+\frac{\epsilon}{2\alpha^A}p_{HH}^2-\frac{\epsilon}{2\alpha^A}p_{LH}p_{HH}-\frac{\epsilon}{\alpha^A}p_{LH}p_{HL}\right\}N\\ =&\left[(2q-1)-\frac{p_{HH}}{\alpha}\right]\frac{p_{HH}(N-2M)}{2}\epsilon+\left(\frac{1}{2}p_{LH}p_{HH}+p_{LH}p_{HL}\right)\frac{N}{\alpha}\epsilon.\end{aligned}$$

Note that

$$\begin{aligned}N-2M&=\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr-2\left(\overline{r}\frac{\alpha^B}{2\alpha^A}-\int_{\underline{r}}^{\overline{r}}F^A(r)\,rdF^B(r)\right)\\ &=\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr-2\left(\overline{r}\frac{\alpha^B}{2\alpha^A}-\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}}F^B(r)\,rdF^B(r)\right)\\ &=\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr-2\left(\overline{r}\frac{\alpha^B}{2\alpha^A}-\frac{\alpha^B}{2\alpha^A}\overline{r}+\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}}\frac{\left(F^B(r)\right)^2}{2}dr\right)\\ &=\int_{\underline{r}}^{\overline{r}}F^B(r)\,dr-\frac{\alpha^B}{\alpha^A}\int_{\underline{r}}^{\overline{r}}\left(F^B(r)\right)^2dr>0.\end{aligned}$$

Therefore, one sufficient condition is

$$2q-1\ge\frac{p_{HH}}{\alpha}=\frac{q\alpha^2+(1-q)(1-\alpha)^2}{\alpha}.$$

[30] We have $p_{HL} = q\alpha^A\left(1-\alpha^B\right)+(1-q)\,\alpha^B\left(1-\alpha^A\right)$ and $p_{LH} = q\left(1-\alpha^A\right)\alpha^B+(1-q)\,\alpha^A\left(1-\alpha^B\right)$ and then therefore $p_{HL}-p_{LH} = q\left(\alpha^A-\alpha^B\right)+(1-q)\left(\alpha^B-\alpha^A\right) = (2q-1)\,\epsilon$.

Collecting terms, the condition above requires $q \geq 1-\alpha+\alpha^2$. Since $1-\alpha+\alpha^2$ increases in α for $\alpha \in \left(\frac{1}{2},1\right)$, this imposes a simple condition that prior needs to be sufficiently good and information technology α cannot be too high.

A.5 Calibration

In this section we explain the details of the empirical moments we use to calibrate parameters $\left\{q,\alpha^A,\alpha^B\right\}$, for both bad news and symmetric signal structures. We fix $\overline{r}=0.36$.

The first two empirical moments that we aim to match are the NPL rates of specialized and non-specialized (stress-tested) banks in our Y14Q.H1 data for stress-tests banks (see Section B for more details). The two NPL rates are 3% (specialized) and 4% (non-specialized) as reported in Table B.1.

The third moment is the average loan approval rate for large U.S. banks (Chart 11 in DeSpain and Pandolfo (2024); we take large banks to be consistent with Y14Q.H1 data which is for large stress test banks). Note this moment is average across banks and loan applications; but since we do not observe the proportions of loans applications that specialized and non-specialized lenders receive, we follow the theory with one specialized bank and one non-specialized bank to assign a weight of half for each bank.

Bad-news information structure. Using results in Appendix A.3.2 and A.4, one can calculate the three model-implied moments under a bad-news information structure to be

$$3\% = \mathbb{P}\left(\theta=0\,\middle|r^A<r^B<\infty\right) = \frac{1}{\frac{q}{1-q}\frac{\frac{1}{2}+\frac{\left[1-F^B(\overline{r})\right]^2}{2}}{(1-\alpha^A)(1-\alpha^B)\left\{\frac{1}{2}+\frac{\left[1-F^B(\overline{r})\right]^2}{2}\right\}+(1-\alpha^A)\alpha^B}+1},$$

$$4\% = \mathbb{P}\left(\theta=0\,\middle|r^B<r^A<\infty\right) = \frac{1}{\frac{q}{1-q}\frac{\frac{1}{2}-\frac{\left[1-F^B(\overline{r})\right]^2}{2}}{(1-\alpha^A)(1-\alpha^B)\left\{\frac{1}{2}-\frac{\left[1-F^B(\overline{r})\right]^2}{2}\right\}+\alpha^A(1-\alpha^B)F^B(\overline{r})}+1},$$

$$0.5 = \frac{1}{2}\mathbb{P}(g^A=H)+\frac{1}{2}\mathbb{P}(g^B=H)F^B(\overline{r}) = \frac{q+(1-q)(1-\alpha^A)}{2}+\frac{[q+(1-q)(1-\alpha^B)]F^B(\overline{r})}{2},$$

where $F^B\left(\overline{r}\right)=\frac{\frac{\overline{r}}{\underline{r}}-1}{\frac{\overline{r}}{\underline{r}}-1+\alpha^A}$ and $\underline{r}=\frac{(1-q)(1-\alpha^B)}{q}$. The resulting calibrated parameters are $\alpha^A=0.984$, $\alpha^B=0.977$, and $q=0.506$, under which $\Delta r=0.26\%$.

Symmetric information structure. Using results in Appendix A.3.2 and A.4, one can calculate the three model-implied moments under a symmetric information structure to be

$$3\% = \mathbb{P}\left(\theta=0\,\middle|r^A<r^B<\infty\right) = \frac{1}{\frac{q}{1-q}\frac{\alpha^A\alpha^B\left[1-F^B(\overline{r})+\frac{\alpha^B}{2\alpha^A}(F^B(\overline{r}))^2\right]+\alpha^A(1-\alpha^B)}{(1-\alpha^A)(1-\alpha^B)\left[1-F^B(\overline{r})+\frac{\alpha^B}{2\alpha^A}(F^B(\overline{r}))^2\right]+(1-\alpha^A)\alpha^B}+1},$$

$$4\% = \mathbb{P}\left(\theta=0\,\middle|r^B<r^A<\infty\right) = \frac{1}{\frac{q}{1-q}\frac{\alpha^A\alpha^B\left[F^B(\overline{r})-\frac{\alpha^B}{2\alpha^A}(F^B(\overline{r}))^2\right]+(1-\alpha^A)\alpha^B F^B(\overline{r})}{(1-\alpha^A)(1-\alpha^B)\left[F^B(\overline{r})-\frac{\alpha^B}{2\alpha^A}(F^B(\overline{r}))^2\right]+\alpha^A(1-\alpha^B)F^B(\overline{r})}+1},$$

$$0.5 = \frac{1}{2}\mathbb{P}(g^A=H)+\frac{1}{2}\mathbb{P}(g^B=H)F^B(\overline{r}) = \frac{q\alpha^A+(1-q)(1-\alpha^A)}{2}+\frac{[q\alpha^B+(1-q)(1-\alpha^B)]F^B(\overline{r})}{2},$$

where

$$F^B\left(\overline{r}\right)=\frac{\alpha^A\overline{r}-\underline{r}}{\alpha^A\alpha^B\overline{r}-\frac{1-q}{q}\left(1-\alpha^A\right)\left(1-\alpha^B\right)},$$

and

$$\underline{r}=\begin{cases}\frac{(1-q)\left(1-\alpha^B\right)}{q}, & \text{if } q\left(1-\alpha^A\right)\alpha^B\overline{r}<(1-q)\,\alpha^A\left(1-\alpha^B\right),\\ \frac{q\alpha^A\left(1-\alpha^B\right)\overline{r}+(1-q)\left(1-\alpha^A\right)\left(1-\alpha^B\right)}{q\alpha^A}, & \text{if } q\left(1-\alpha^A\right)\alpha^B\overline{r}\geq(1-q)\,\alpha^A\left(1-\alpha^B\right).\end{cases}$$

The resulting calibrated parameters are $\alpha^A = 0.984$, $\alpha^B = 0.977$, and $q = 0.510$, under which $\Delta r = 0.17\%$.

Non-zero recovery rate. We have solved the model with non-zero recovery in Appendix A.3. For calibration we set the recovery to be $\delta = 0.6$ which is about the average recovery rate in the Y-14 data (including all types of collateral). We then recalibrate our three parameters for canonical models.

Importantly, a positive recovery does not affect the functional forms of the key empirical moments and they are still the same as above. However, endogenous equilibrium variables such as $F^B(\overline{r})$ which enter these moments is a function of recovery rate δ. For instance, for bad-news information structure, $F^B(\overline{r}) = \frac{\alpha^A\overline{r}-\underline{r}}{\alpha^A\alpha^B\overline{r}-\frac{1-q}{q}(1-\alpha^A)(1-\alpha^B)} = \frac{\overline{r}-\frac{(1-q)\left(1-\alpha^B\right)(1-\delta)}{q}}{\overline{r}-\frac{(1-q)(1-\alpha^A)(1-\alpha^B)(1-\delta)}{q}}$; the resulting calibrated parameters are the calibrated parameters are $q = 0.5006$, $\alpha^A = 0.9843$, $\alpha^B = 0.9789$ which yield a positive interest rate wedge of $\Delta r = 4\times10^{-4}$.

A.6 Proof of Proposition 3

Proof. Based on the credit competition equilibrium in Proposition 1, the expected rates of a lender's issued loan are:

$$\mathbb{E}\left[r^A\middle|\,r^A<r^B\leq\infty\right]=\frac{\underbrace{p_{HH}}_{g^A=g^B=H}\int_x^1\underbrace{\left[1-F^B\left(r^A(t)^-\right)\right]}_{A\text{ wins}}r^A(t)\,\phi(t)\,dt+\underbrace{p_{HL}}_{g^A=L,g^B=L}\int_x^1 r^A(t)\,\phi(t)\,dt}{p_{HH}\int_x^1\left[1-F^B\left(r^A(t)^-\right)\right]\phi(t)\,dt+p_{HL}\int_x^1\phi(t)\,dt},$$

$$\mathbb{E}\left[r^B\middle|\,r^B<r^A\leq\infty\right]=\frac{\underbrace{p_{HH}}_{g^A=g^B=H}\int_{\hat{s}}^1\underbrace{\Phi(t)}_{B\text{ wins}}r(t)\,d\left[-F^B(r(t))\right]+\underbrace{p_{LH}}_{g^A=L,g^B=H}\int_x^1 r(t)\,d\left[-F^B(r(t))\right]}{p_{HH}\int_{\hat{s}}^1\Phi(t)\,d\left[-F^B(r(t))\right]+p_{LH}F^B(\overline{r})}.$$

In positive weak equilibrium, $F^B(r(s))$ has a point mass of size $1-F^B\left(\overline{r}^-\right)$ at $\overline{r}$ or $r^A(\hat{s})$.

In this proposition, we impose the following conditions a) general signals are degenerate with $q_g = 1$ and b) $\overline{r}\to\infty$. (The logic for $\alpha_u = \alpha_d = 0.5$ so that lenders ignore the general signals are the same.) Then

$$\mathbb{E}\left[r^A+1\middle|\,r^A<r^B\leq\infty\right]=\frac{\int_0^1\left[1-F^B\left(r^A(t)^-\right)\right]r^A(t)\,\phi(t)\,dt}{\int_0^1\left[1-F^B\left(r^A(t)^-\right)\right]\phi(t)\,dt}=\frac{\int_0^1\Phi(t)\,\phi(t)\,dt}{\int_0^1\left[\int_0^t\nu\phi(\nu)\,d\nu\right]\phi(t)\,dt},$$

$$\mathbb{E}\left[r^B+1\middle|\,r^B<r^A\leq\infty\right]=\frac{\int_0^1\Phi(t)\,r(t)\,d\left[-F^B(r(t))\right]}{\int_0^1\Phi(t)\,d\left[-F^B(r(t))\right]}=\frac{\int_0^1\Phi(t)\left[\frac{t\Phi(t)}{\int_0^t\nu\phi(\nu)d\nu}\right]\phi(t)\,dt}{\int_0^1\Phi(t)\,t\phi(t)\,dt},$$

where the first equality of both variables uses condition a) degenerate signals and $x = \hat{s} = 0$ which follows from condition b), and the second equality uses equilibrium strategy $r^A(t) = \frac{\Phi(s)}{\int_0^s t\phi(t)dt}$ and $1 - F^B\left(r^A(t)^-\right) = \frac{\int_0^t\nu\phi(\nu)dt}{q_s}$.

Additionally, c) the specialized signal distribution is $\phi(s) = 1 + \epsilon [2 \cdot \mathbf{1}_{s \leq 0.5} - 1]$. Then

$$\mathbb{E}\left[r^A + 1 \middle| r^A < r^B \leq \infty \right] = 2 \cdot \frac{\frac{1}{8}(1+\epsilon)^2 + \frac{\epsilon(1-\epsilon)}{2} + \frac{3}{8}(1-\epsilon)^2}{\frac{1}{24}(1+\epsilon)^2 + \frac{\epsilon(1-\epsilon)}{4} + \frac{7}{24}(1-\epsilon)^2},$$

$$\mathbb{E}\left[r^B + 1 \middle| r^B < r^A \leq \infty \right] = 2 \cdot \frac{\frac{1}{8}(1+\epsilon)^2 + \frac{\epsilon(1-\epsilon)}{2} + \frac{3}{8}(1-\epsilon)^2 + \epsilon^2(1-\epsilon)\int_{0.5}^{1} \frac{\left(t-\frac{1}{2}\right)}{\frac{\epsilon}{2}+(1-\epsilon)t^2} dt + \epsilon(1-\epsilon)^2 \int_{0.5}^{1} \frac{t\left(t-\frac{1}{2}\right)}{\frac{\epsilon}{2}+(1-\epsilon)t^2} dt}{\frac{1}{24}(1+\epsilon)^2 + \frac{3\epsilon(1-\epsilon)}{8} + \frac{7}{24}(1-\epsilon)^2}.$$

Note that when $\epsilon = 0$, $\Delta r = 0$. When $\epsilon \to 0$, we have (ignoring higher order terms of ϵ)

$$\frac{\partial \Delta r}{\partial \epsilon} = \lim_{\epsilon \to 0} \frac{\Delta r(\epsilon)}{\epsilon} = \frac{1}{\epsilon}\left(\frac{1}{\frac{1}{3} - \frac{1}{4}\epsilon} - \frac{1 + \epsilon - \epsilon \ln 2}{\frac{1}{3} - \frac{1}{8}\epsilon} \right) = 3 \ln 2 - \frac{15}{8} > 0.$$

Hence, when $\epsilon > 0$ ($\epsilon < 0$), i.e., $\phi(s)$ tilts toward less (more) favorable realizations, we have $\Delta r > 0$ ($\Delta r < 0$). $\square$

A.7 Information Acquisition

In this section, we characterize the incentive compatibility condition and lending profits and then provide a numerical illustration in which the specialization equilibrium arises.

Incentive compatibility conditions. Banks make their information acquisition decisions simultaneously, and we assume that information acquisition is observable when banks enter the credit market competition game. Therefore a lender's deviation from the proposed equilibrium information acquisition will lead to a different information structure in the credit market competition, and we need to derive equilibrium lending profits in all possible subgames following a deviation.

Denote by $\Pi_j^i(I_A^g, I_A^s, I_B^s, I_B^s)$ the expected lending profits of bank j in firm i when the information structure in firm i is given by $(I_A^g, I_A^s, I_B^g, I_B^s,)$, where I_j^g and I_j^s take value of one if bank j acquired general and specialized signals in firm i, respectively, and zero otherwise. The symmetry on industries implies that a bank's expected lending profits in firm i only depend on the information structure in that industry but not on the industry itself, i.e.,

$$\Pi_j^a(I_A^g, I_A^s, I_B^s, I_B^g) = \Pi_j^b(I_A^g, I_A^s, I_B^g, I_B^s). \tag{48}$$

Therefore, we drop index i from the expected lending profits. Moreover, we focus on Bank A's incentives in what follows since the no deviation conditions for banks A and B are symmetric.

Bank A can deviate along three dimensions: it can choose not to acquire general information, it can choose not to acquire specialized information about firm a, and it can choose to acquire specialized information in firm b. Bank A's incentives to deviate along these dimensions will depend on the costs of acquiring information. As one would expect, the lower the cost of acquiring general information, the more likely Bank A has incentives to acquire general information and not deviate along this dimension. For deviations along the specialized information dimension, the cost of acquiring specialized information has to be low enough such that it is worth acquiring specialized information in firm a and having an informational advantage over Bank B in this firm but high enough such that it is not worth acquiring specialized information in firm b to stop being the less informed lender. This intuition can be formally stated in the following incentive compatibility constraints. Bank A does not want to deviate by

1. not acquiring general information:

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)-\Pi_A\left(I_A^g=0,I_A^s=1,I_B^g=1,I_B^s=0\right)+$$
$$\Pi_A\left(I_A^g=1,I_A^s=0,I_B^g=1,I_B^s=1\right)-\Pi_A\left(I_A^g=0,I_A^s=0,I_B^g=1,I_B^s=1\right)\geq\kappa_g; \tag{G}$$

2. not acquiring general information nor specialized information in firm a:

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)-\Pi_A\left(I_A^g=0,I_A^s=0,I_B^g=1,I_B^s=0\right)+$$
$$\Pi_A\left(I_A^g=1,I_A^s=0,I_B^g=1,I_B^s=1\right)-\Pi_A\left(I_A^g=0,I_A^s=0,I_B^g=1,I_B^s=1\right)\geq\kappa_g+\kappa_s; \tag{NI}$$

3. not acquiring specialized information in firm a:

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)-\Pi_A\left(I_A^g=1,I_A^s=0,I_B^g=1,I_B^s=0\right)\geq\kappa_s; \tag{Sa}$$

4. and, acquiring specialized information in firm b:

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=1\right)-\Pi_A\left(I_A^g=1,I_A^s=0,I_B^g=1,I_B^s=1\right)\leq\kappa_s. \tag{NSb}$$

Essentially, constraints (G) and (NI) impose an upper bound on κ_g so that Bank A wants to acquire general information. Analogously, constraints (NI) and (Sa) impose an upper bound on κ_s so that Bank A wants to acquire specialized information in firm a, while Constraint (NSb) imposes a lower bound on κ_s to ensure it does not want to be specialized in firm b.

Lending Profits

We characterize lending profits as a function of information acquisition, $\Pi_A\left(I_A^g,I_A^s,I_B^g,I_B^s\right)$ (we focus on Bank A due to symmetry.) We omit the case where there is an uninformed lender.

$\mathbf{I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0}$ **(Specialization).** This is the equilibrium that we focus on—each lender has a general information signal and only Bank A has a specialized signal s. Bank A's expected lending profit before signal realizations is thus

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)=\int_x^1\pi^A\left(r^A\left(s\right)\middle|\,s\right)\phi\left(s\right)ds,$$

where $\pi^A\left(r^A\left(s\right)\middle|\,s\right)$ is the profits for given signal realizations H and s and is given in Eq. (9). Using the equilibrium strategies in Proposition 1, we have

$$\pi^A\left(r^A\left(s\right)\middle|\,s\right)=p_{HH}\cdot\frac{\int_0^{\max\{s,\hat{s}\}}\left(s-t\right)\phi\left(t\right)dt}{q_s}+\left(\pi^B+p_{LH}\right)\cdot\frac{s}{q_s}-p_{HL},\ \text{for } s\geq x.$$

The expression shows that Bank A earns the information rent from the specialized signal. Bank A observes s, while Bank B may only negatively update the prior q_s when winning the competition that $s^A\leq s\left(r\right)$; this is reflected in the terms $\frac{s}{q_s}$ and $\frac{\int_0^{\min\{s,\hat{s}\}}(s-t)\phi(t)dt}{q_s}$.

In this case, Bank B's profit $\Pi_B\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)=\pi^B$ is given in Lemma 2. By symmetry, $\Pi_A\left(I_A^g=1,I_A^s=0,I_B^g=1,I_B^s=1\right)=\Pi_B\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=0\right)=\pi^B$.

$\mathbf{I_A^g = 0, I_A^s = 1, I_B^g = 1, I_B^s = 0}$ **(Asymmetric technology).** In this case, Bank A only collects specialized information while Bank B only collects general information in industry a. This case is nested in the previous case of specialization ($I_A^g = 1, I_A^s = 1, I_B^g = 1, I_B^s = 0$), by reformulating Bank A to have an uninformative general signal, e.g.,

$$\mathbb{P}\left(g^A = H \middle| \theta_g = 1\right) = \mathbb{P}\left(g^A = H \middle| \theta_g = 0\right) = 1.$$

$\mathbf{I_A^g = 1, I_A^s = 0, I_B^g = 1, I_B^s = 0}$ **(General information only).** In this case, both lenders only acquire general information, i.e., investing in IT and data processing that apply to both industries. The credit competition corresponds to Broecker (1990) with two lenders. Lenders are symmetric and the lending profit of, say Bank A, is

$$\Pi_A\left(I_A^g = 1, I_A^s = 0, I_B^g = 1, I_B^s = 0\right) = \max\left\{p_{HL}\left(\mu_{HL} q_s \overline{r} - 1\right), 0\right\}.$$

The "max" operator arises because either both lenders withdraw with positive probability (zero profits), or both lenders make profits and neither has a point mass at $\overline{r}$, i.e., $F^j\left(\overline{r}^-\right) = 1$.

$\mathbf{I_A^g = 1, I_A^s = 1, I_B^g = 1, I_B^s = 1}$ **(Acquire all information).** In this symmetric case, each lender invests in both information technologies and receives both the general and specialized signals. We characterize the credit market equilibrium based on Riordan (1993) which considers the competition between two lenders each with a continuous private signal. Here, each lender additionally has a binary signal that represents the general information. Following the modeling of Riordan (1993), we work with the direct specialized signal z. Specifically, let z and Z denote the realization and the random variable of the specialized signal respectively, and let

$$\tilde{F}(z) \equiv \mathbb{P}\left(Z \le z \middle| \theta_s = 1\right),\ \tilde{G}(z) \equiv \mathbb{P}\left(Z \le z \middle| \theta_s = 0\right)$$

denote the CDFs of Z conditional on the underlying state θ_s, with the corresponding PDFs denoted by $\tilde{f}$ and $\tilde{g}$. Introduce $\mu(z) \equiv \mathbb{P}\left(\theta_s = g \middle| S\right)$ as the posterior belief, which is s in our baseline model.

A lender only bids when the general signal is H and the specialized signal $z \ge x$. Let $R(z) \equiv r(z) + 1$ denote the equilibrium gross rate quote. Given competitor's strategy $R(z)$, the lending profits from any R is then

$$\begin{aligned}\pi\left(R \,|z\right) = {} & \left[p_{HH}\mu_{HH}\mu(z)\tilde{F}(t(R)) + p_{HL}\mu_{HL}\mu(z)\right]R \\ & - p_{HH}\left[(1-\mu(z))\tilde{G}(t(R)) + \mu(z)\tilde{F}(t(R))\right] - p_{HL},\end{aligned} \tag{49}$$

where $t(R)$ the signal such that the other bank offers R. The first order condition w.r.t. R is

$$\begin{aligned}\frac{\partial \pi\left(R(t)\,|z\right)}{\partial R} = {} & \left[p_{HH}\mu_{HH}\mu(z)\tilde{F}(t) + p_{HL}\mu_{HL}\mu(z)\right] \\ & + \left\{p_{HH}\mu_{HH}\mu(z)\tilde{f}(t)R(t) - p_{HH}\left[(1-\mu(z))\tilde{g}(t) + \mu(z)\tilde{f}(t)\right]\right\}\frac{dt}{dR}.\end{aligned}$$

The equilibrium strategy satisfies

$$\left.\frac{\partial \pi\left(R(t)\,|z\right)}{\partial t}\right|_{t=z} = 0.$$

By symmetry, we have

$$\frac{dt}{dR} = \frac{1}{R'(t)}.$$

These two conditions imply

$$p_{HH}\mu_{HH}\tilde{f}(z)R(z)+\left(p_{HH}\mu_{HH}\tilde{F}(z)+p_{HL}\mu_{HL}\right)R'(z)=\frac{p_{HH}(1-\mu(z))\tilde{g}(z)+p_{HH}\mu(z)\tilde{f}(z)}{\mu(z)},\tag{50}$$

or equivalently,

$$\frac{d\left\{\left[p_{HH}\mu_{HH}\tilde{F}(z)+p_{HL}\mu_{HL}\right]R(z)\right\}}{dz}=\frac{p_{HH}(1-\mu(z))\tilde{g}(z)+p_{HH}\mu(z)\tilde{f}(z)}{\mu(z)}.$$

Integrating over z, we have

$$R(z)=\frac{\int_{\underline{z}}^{z}\frac{p_{HH}(1-\mu(t))\tilde{g}(t)+p_{HH}\mu(t)\tilde{f}(t)}{\mu(t)}dt+constant}{p_{HH}\mu_{HH}\tilde{F}(z)+p_{HL}\mu_{HL}}.\tag{51}$$

The unknown constant is pinned down by the boundary condition $\pi(\overline{r}+1|x)=0$: Upon the threshold signal x, a lender quotes the maximum interest rate $\overline{r}+1$ and makes zero profit,

$$0=\left[p_{HH}\mu_{HH}\mu(x)\tilde{F}(x)+p_{HL}\mu_{HL}\mu(x)\right](\overline{r}+1)-p_{HH}\left[(1-\mu(x))\tilde{G}(x)+\mu(x)\tilde{F}(x)\right]-p_{HL}.\tag{52}$$

Then a lender's lending profit is

$$\Pi_A\left(I_A^g=1,I_A^s=1,I_B^g=1,I_B^s=1\right)=\int_x^{\overline{z}}\pi\left(R(z)|\,z\right)\left[q_s\tilde{f}(z)+(1-q_s)\tilde{g}(z)\right]dz,$$

where $R(z)$ is given by Eq. (51) and (52), profit $\pi(R(z),z)$ is given by Eq. (49).

A.8 Generalized Information Structure

It is convenient to work with the direct specialized signal z (now posterior s may depend on the realizations of the general signals). We focus on the well-behaved structure (i.e., smooth distribution of interest rates over $[\underline{r},\overline{r})$ and decreasing $r^A(z)$) and show that the lender strategies in Proposition 4 correspond to an equilibrium. We impose the following primitive conditions under which the general signal is decisive.

Assumption 2. *i) Bank A rejects the borrower upon an L general signal, regardless of any specialized signal z:*

$$\mu_{L\cdot}(\overline{z})(\overline{r}+1)-1<0.\tag{53}$$

ii) Bank B is willing to participate if and only if its general signal $g^B=H$:

$$\int_{\underline{z}}^{\overline{z}}p_{\cdot H}(t)\left[\mu_{\cdot H}(t)(\overline{r}+1)-1\right]dt>0.\tag{54}$$

Consider a specialized signal $z\sim\phi_z(z)$ for $z\in[\underline{z},\overline{z}]$ where both $\underline{z}$ and $\overline{z}$ can be unbounded. Denote by $\mu_{g^Ag^B}(z)\equiv\mathbb{P}\left(\theta=1\left|g^A,g^B,z\right.\right)$ the posterior probability density for $\theta=1$, i.e., the state of project success. Without loss of generality, we assume that $\mu_{HH}(z)$ strictly increases in z (as we can always use $\mu_{HH}(z)$ as a signal; recall the posterior s serves as the signal in the baseline model given in Section 2). This implies that just as in the baseline, there exists $\hat{z}$ at which Bank A starts quoting $\overline{r}$, and z_x below which it starts rejecting borrowers. Let $\overline{\mu}_{g^Ag^B}\equiv\mathbb{P}\left(\theta=1|\,g^A,g^B\right)$ denote the posterior probability of $\theta=1$ based on general signals.

Let $p_{g^Ag^B}(z)\equiv\mathbb{P}\left(g^A,g^B,z\right)$, $\overline{p}_{g^Ag^B}\equiv\mathbb{P}\left(g^A,g^B\right)$, and $\alpha_u^j\equiv\mathbb{P}\left(g^j=H\right|\theta=1)$ for $j\in\{A,B\}$ (so two lenders can differ in their precisions in general signals). Finally, let $\phi_z(z|\theta=1)$ be the density of z conditional on $\theta=1$. The following proposition generalizes Proposition 1 by showing that the simple equilibrium structure survives under the more generalized information structure. This is because lenders only consider the marginal good type borrower who is payoff relevant, so the key argument in the baseline model still applies given signals' independence conditional on project success. As a result, the effects of specialized and general signals on equilibrium strategies are separable, and a simple characterization as in Proposition 4 ensues.

Proposition 4. ***(Credit Market Equilibrium under General Information Structure)*** *Lender $j \in \{A,B\}$ rejects the borrower (by quoting $r=\infty$) upon $g^j=L$; when $g^j=H$, lender j may make offers from a common support $[\underline{r},\overline{r}]$ (or reject) with the following properties.*

1. *Bank A who observes a specialized signal z offers*

$$r^A(z)=\begin{cases}\min\left\{\frac{\pi^B+\int_{\underline{z}}^{z}p_{HH}(t)dt+\overline{p}_{LH}}{\int_{\underline{z}}^{z}p_{HH}(t)\cdot\mu_{HH}(t)dt+\overline{p}_{LH}\overline{\mu}_{LH}}-1,\overline{r}\right\}, & \text{for} \quad z\in[z_x,\overline{z}]\\ \infty, & \text{for} \quad z\in[\underline{z},z_x).\end{cases} \tag{55}$$

This equation pins down $\underline{r}=r^A(\overline{z})$, $\hat{z}=\sup\left\{z:r^A(z)=\overline{r}\right\}$, and $z_x=\sup\left\{z:r^A(z)=\infty\right\}$.

2. *Bank B makes an offer by randomizing its rate according to:*

$$F^B(r)=\begin{cases}\frac{\alpha_u^A}{\alpha_u^B}\left[1-\int_{\underline{z}}^{z^A(r)}\phi_z(t|\theta=1)\,dt\right], & \text{for} \quad r\in[\underline{r},\overline{r}),\\ 1-\mathbf{1}_{\{\pi^B=0\}}\cdot\left\{1-\frac{\alpha_u^A}{\alpha_u^B}\left[1-\int_{\underline{z}}^{\hat{z}}\phi_z(t|\theta=1)\,dt\right]\right\}, & \text{for} \quad r=\overline{r}.\end{cases} \tag{56}$$

3. *The endogenous non-specialized Bank B's profit $\pi^B\geq 0$ is determined similarly as Lemma 2, with detailed expression provided in Appendix A.8.*

Proof. Similar as the derivation in the baseline model, we first take π^B as given to characterize lender strategy, and then solve for π^B.

Bank A's strategy

In the region of $z\in(\hat{z},1]$ that corresponds to $r^A(z)\in[\underline{r},\overline{r})$, $r^A(\cdot)$ is strictly decreasing so the inverse function $z^A(\cdot)\equiv r^{A(-1)}(\cdot)$ is properly defined. Bank B's lending profit when quoting $r\in[\underline{r},\overline{r})$ is

$$\begin{aligned}\pi^B(r)&=\underbrace{\overline{p}_{HH}}_{g^A=H}\cdot\underbrace{\int_{\underline{z}}^{z^A(r)}}_{B\text{ wins}}\left[\underbrace{\mu_{HH}(t)}_{\text{repay}}(1+r)-1\right]\phi_z(t|HH)\,dt+\underbrace{\overline{p}_{LH}}_{g^A=L}\left[\underbrace{\overline{\mu}_{LH}}_{\text{repay}}(1+r)-1\right]\\&=(1+r)\left[\int_{\underline{z}}^{z^A(r)}p_{HH}(t)\,\mu_{HH}(t)\,dt+\overline{p}_{LH}\overline{\mu}_{LH}\right]-\int_{\underline{z}}^{z^A(r)}p_{HH}(t)\,dt-\overline{p}_{LH}\end{aligned} \tag{57}$$

Bank A's equilibrium strategy $r^A(z)$ for $z \in [\hat{z}, 1]$ is such that Bank B is indifferent across $r \in [\underline{r}, \overline{r})$. Hence,

$$r^A(z) = \frac{\overbrace{\pi^B + \int_{\underline{z}}^{z} p_{HH}(t)\, dt + \overline{p}_{LH}}^{B\text{'s lending amount}}}{\underbrace{\int_{\underline{z}}^{z} p_{HH}(t) \cdot \mu_{HH}(t)\, dt + \overline{p}_{LH}\overline{\mu}_{LH}}_{B\text{'s customers who repay}}} - 1, \quad \text{where} \quad \hat{z} \leq s \leq \overline{z}. \tag{58}$$

Note that this pins down $\underline{r} = (r^A)^{-1}(\overline{z})$ which is a function of π^B.

In addition, $r^A(z) = \overline{r}$ for $z \in [z_x, \hat{z})$ and Bank A rejects the borrower when $z \in [\underline{z}, z_x)$, where z_x satisfies

$$\pi^A\left(r^A(z_x) = \overline{r} \middle| z_x\right) = 0.$$

This completes the proof of Bank A's strategy in Proposition 4.

Bank B's strategy

Bank A's offered interest rate $r^A(z)$ upon $z \in [\hat{z}, \overline{z}]$ maximizes

$$\pi^A\left(r^A(z) \middle| z\right) = \underbrace{p_{HH}(z)}_{g^B=H} \underbrace{\left[1 - F^B(r)\right]}_{A \text{ wins}} \left[\underbrace{\mu_{HH}(z)}_{\text{repay}}(1+r) - 1\right] + \underbrace{p_{HL}(z)}_{g^B=L} \left[\underbrace{\mu_{HL}(z)}_{\text{repay}}(1+r) - 1\right]$$

The FOC with respect to r is

$$\underbrace{\left[-\frac{d\left[F^B(r)\right]}{dr}\right]}_{\Delta\text{winning prob}} \underbrace{p_{HH}(z)\left[\mu_{HH}(z)(1+r) - 1\right]}_{\text{profit upon winning}} + \underbrace{p_{HH}(z)\left[1 - F^B(r)\right]\mu_{HH}(z) + p_{HL}(z)\mu_{HL}(z)}_{\text{existing customer}} = 0.$$

Bank A's optimal strategy $r^A(z)$ satisfies this first-order condition,

$$\begin{aligned} 0 = &-\frac{d\left[F^B\left(r^A(z)\right)\right]}{dr} p_{HH}(z)\left[\mu_{HH}(z)\left(1 + r^A(z)\right) - 1\right] \\ &+ p_{HH}(z)\left[1 - F^B\left(r^A(z)\right)\right]\mu_{HH}(z) + p_{HL}(z)\mu_{HL}(z). \end{aligned} \tag{59}$$

From Eq. (58) about $r^A(z)$, we derive the following key equation by taking derivatives w.r.t. z,

$$\underbrace{\frac{dr^A(z)}{dz}\left[\int_{\underline{z}}^{z} p_{HH}(t)\mu_{HH}(t)\, dt + \overline{p}_{LH}\overline{\mu}_{LH}\right]}_{\text{B: }\uparrow\text{marginal customer return}} + \underbrace{p_{HH}(z)\left[\left(r^A(z) + 1\right)\mu_{HH}(z) - 1\right]}_{\text{B: }\uparrow\text{existing customer revenue}} = 0.$$

Plug this equation into the FOC (59), and we have

$$-\frac{d\left[F^B\left(r^A(z)\right)\right]}{dz}\left[\int_{\underline{z}}^{z} p_{HH}(t)\mu_{HH}(t)\, dt + \overline{p}_{LH}\overline{\mu}_{LH}\right] = p_{HH}(z)\left[1 - F^B(r)\right]\mu_{HH}(z) + p_{HL}(z)\mu_{HL}(z),$$

which is equivalent to

$$\frac{d}{dz}\left\{\frac{1 - F^B\left(r^A(z)\right)}{\int_{\underline{z}}^{z}\mu_{HH}(t)p_{HH}(t)\, dt + \overline{p}_{LH}\overline{\mu}_{LH}}\right\} = \frac{p_{HL}(z)\mu_{HL}(z)}{\left[\int_{\underline{z}}^{z} p_{HH}(t)\mu_{HH}(t)\, dt + \overline{p}_{LH}\overline{\mu}_{LH}\right]^2}. \tag{60}$$

Since signals are independent conditional on the state being $\theta = 1$, the right-hand-side equals

$$\frac{q\mathbb{P}\left(HL|\,\theta=1\right)\phi_z\left(z|\,\theta=1\right)}{\left[\int_{\underline{z}}^{z} q\mathbb{P}\left(HH|\,\theta=1\right)\phi_z\left(t|\,\theta=1\right)dt+\overline{p}_{LH}\overline{\mu}_{LH}\right]^2}$$
$$=-\frac{\mathbb{P}\left(g^B=L\middle|\,\theta=1\right)}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}\frac{d}{dz}\left[\frac{1}{\int_{\underline{z}}^{z} q\mathbb{P}\left(HH|\,\theta=1\right)\phi_z\left(t|\,\theta=1\right)dt+\overline{p}_{LH}\overline{\mu}_{LH}}\right].$$

Then the solution $F^B\left(r^A\left(z\right)\right)$ to the ODE (60) satisfies

$$\frac{1-F^B\left(r^A\left(z\right)\right)}{\int_{\underline{z}}^{z}\mu_{HH}\left(t\right)p_{HH}\left(t\right)dt+\overline{p}_{LH}\overline{\mu}_{LH}}=-\frac{\mathbb{P}\left(g^B=L\middle|\,\theta=1\right)}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}\left[\frac{1}{\int_{\underline{z}}^{z}\mu_{HH}\left(t\right)p_{HH}\left(t\right)dt+\overline{p}_{LH}\overline{\mu}_{LH}}\right]+Const.$$

Using the boundary condition $F^B\left(r^A\left(\overline{z}\right)=\underline{r}\right)=0$, we solve for the constant

$$Const=\frac{1}{\mathbb{P}\left(\theta=1\right)}\frac{1}{\mathbb{P}\left(g^B=H|\,\theta=1\right)^2}.$$

Therefore,

$$F^B\left(r\right)=\frac{1}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}-\frac{\int_{\underline{z}}^{z^A(r)}\mu_{HH}\left(t\right)p_{HH}\left(t\right)dt+\overline{p}_{LH}\overline{\mu}_{LH}}{\mathbb{P}\left(\theta=1\right)\mathbb{P}\left(g^B=H|\,\theta=1\right)^2}$$
$$=\frac{1}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}-\frac{\mathbb{P}\left(\theta=1\right)\mathbb{P}\left(HH|\,\theta=1\right)\int_{\underline{z}}^{z^A(r)}\phi_z\left(t|\,\theta=1\right)dt+\mathbb{P}\left(\theta=1\right)\mathbb{P}\left(LH|\,\theta=1\right)}{\mathbb{P}\left(\theta=1\right)\mathbb{P}\left(g^B=H|\,\theta=1\right)^2}$$
$$=\frac{\mathbb{P}\left(g^A=H\middle|\,\theta=1\right)}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}\left[1-\int_{\underline{z}}^{z^A(r)}\phi_z\left(t|\,\theta=1\right)dt\right].$$

Bank B's profit π^B

Now we are left with one unknown variable π^B in Eq. (58). Similar to the baseline model, the equilibrium could be positive-weak or zero-weak, depending on who—Bank A receiving threshold specialized signal z_A^{be} and quoting $\overline{r}$ or Bank B—breaks even first in competition. We define z_A^{be} and z_B^{be} as

$$0=\pi^A\left(\overline{r}\,\middle|z_A^{be}\right)=p_{HH}\left(z_A^{be}\right)\frac{\mathbb{P}\left(g^A=H\middle|\,\theta=1\right)}{\mathbb{P}\left(g^B=H|\,\theta=1\right)}\left[1-\int_{\underline{z}}^{z_A^{be}}\phi_z\left(t|\,\theta=1\right)dt\right]\cdot\left[\mu_{HH}\left(z_A^{be}\right)\left(1+\overline{r}\right)-1\right]$$
$$+p_{HL}\left(z_A^{be}\right)\left[\mu_{HL}\left(z_A^{be}\right)\left(1+\overline{r}\right)-1\right],$$
$$0=\pi^B\left(\overline{r};z_B^{be}\right)=\int_{\underline{z}}^{z_B^{be}}p_{HH}\left(t\right)\mu_{HH}\left(t\right)\left(1+\overline{r}\right)dt-\int_{\underline{z}}^{z_B^{be}}p_{HH}\left(t\right)dt+\overline{p}_{HL}\left[\overline{\mu}_{HL}\left(1+\overline{r}\right)-1\right].$$

Equilibrium π^B is then

$$\pi^B=\max\left\{\int_{\underline{z}}^{z_A^{be}}p_{HH}\left(t\right)\mu_{HH}\left(t\right)\left(1+\overline{r}\right)dt-\int_{\underline{z}}^{z_A^{be}}p_{HH}\left(t\right)dt+\overline{p}_{HL}\left[\overline{\mu}_{HL}\left(1+\overline{r}\right)-1\right],0\right\}.$$

When $z_A^{be}>z_B^{be}$, equilibrium is positive weak with $\pi^B>0$, and $\hat{z}=z_x=z_A^{be}$; when $z_A^{be}\leq z_B^{be}$, equilibrium is zero weak with $\pi^B=0$, and $z_B^{be}=\hat{z}>z_x$. □

B Empirical Analysis

B.1 Data

We use Y14Q-H.1 data that is collected by the Federal Reserve System as part of its stress-testing efforts, covering all C&I loans to which a stress-tested bank has committed more than 1 million USD (around 75% of all U.S. C&I lending). As such, the data covers 40 banks – in an unbalanced panel – between 2011 and 2023 and includes millions of loan-quarter observations.

We focus on term loans and limit our sample to loans that are likely newly originated or new to the lender. We cut our data before 2012 to avoid accidentally labeling a loan as "newly originated," simply because of the point at which the data collection begins. We define a loan as new when it first appears in our data. We remove loans to financial or insurance entities. Our final sample covers 350,000 new term loans. Besides loan amount, we can track key loan data such as the interest rate paid by the borrower, the loan's purpose, and the performance of the loan while it remains in our sample, as we can see if it ever falls into arrears.

B.2 Statistics

Key summary statistics for loans in our sample are outlined in Table B.1. The average loan commitment in our sample is just over 12 million USD in size and the average loan interest rate is 3.7%. We define a loan as non-performing if it is ever 90+ days in arrears, ever has negative maturity (i.e. has not been repaid at maturity), or has outright defaulted. We then take a loan as "ever" non-performing if it becomes so at any point after origination. The percentage of non-performing loans is around 4% in our data, which is slightly higher than the average default rate given our wider definition.

As we have explained in Section 4.4, we do not have data on firm characteristics typically used by banks to assess a loan's risk. Hence, to sidestep this issue, we use three rating categories (high-risk, mid-risk, and low-risk) based on the banks' internal ratings of a loan to proxy for observable loan qualities. Banks report loan risk on a scale of 1-10. We have created terciles (1-3), which allow us account for whether a loan is high, medium, or low risk without relying on bank-specific knowledge. For the subsample for which we have firm characteristics, however, we can confirm that our three risk categories capture aspects linked to (prior) expected loan quality. Table B.2 shows the average borrower Debt/EBITDA, return on assets, and assets-to-debt for each of the three loan risk categories we use as risk metrics in our baseline regression. For instance, as expected, the high-risk category with Rating 3 has the highest Debt/EBITDA, lowest RoA, and lowest asset-to-debt.

B.3 Alternative Risk Controls

We can show that our results are not determined by the construction of our risk controls (see above). Instead of dummies for three risk categories, for instance, we can instead make use of dummies for the exact risk assigned to a loan by the lending bank. This gives us 10 dummies for the risk groups 1-10. Alternatively, in regressions that make use of whether a loan ever becomes non-accruing as a dependent variable, we are able to make use of the rate charged as a proxy for loan risk instead. We show the results of these specification in Table B.3. In columns (1)-(3), where we relate the rate charged to bank specialization, we make use of dummies (1-10) for loan risk. In columns (4)-(6) we make use of the interest rate as a control. Interest rates may reflect the market's or a bank's public view of a loan's riskiness. As can be seen, our results are unaffected by the choice of risk control. In Panel B of Table B.3 we make use of firm characteristics for the subsample of firms that report these data to their Y14 lenders. This reduces our sample by 50%. Nevertheless, we can again show that our results are unaffected by the choice of risk control.

B.4 4-Digit NAICS Industry

We define an industry using NAICS codes. The two digit NAICS-level yields 23 distinct industries for our purposes. We argue that the types of contracts and the types of collateral associated with such contracts – as well as the type of monitoring necessary to ensure contract compliance – is similar across a given two digit industry[31]. However, 23 industries may be seen as too coarse in some instances. After all, some sectors may encompass very different types of firms. We can test our propositions at the 4 digit level instead of the 2 digit level. Using 4-digit NAICS codes, we have a far greater degree of granularity with 310 industries. Specialization at this granular level is much narrower. We define a bank as specialized at the 4-digit level if it is 1% over-invested relative to what would be assumed under diversification. This is equivalent to having levels of over-investment equivalent to being in the top 20% of over-investment by Y14 lenders at any given time in any industry. As can be seen from Table B.4, our baseline results, discussed above, are confirmed. A specialized lender is likely to charge 170 basis points less (column (3)) and experience 0.7% fewer defaults. The effects are somewhat smaller at the 4-digit – relative to the 2-digit – level given some noise at this granularity. Lender specialization may be somewhat less stable.

B.5 The COVID Period

We have included the period between 2020 and 2021 in our analyses discussed in Section 4, above. We recognize that this period may be unique in recent history, given the large-scale interventions that sought to help banks extend credit to shuttered businesses. As can be seen in Table B.5, we are able to exclude these years from our data without affecting our analyses. Our coefficients are not statistically different from those in the baseline regression. The COVID period neither drove nor severely impacted the difference between specialized and non-specialized banks. Lenders charge lower rates to borrowers in the industry in which they specialize without suffering worse loan performance as a consequence in both COVID and non-COVID periods.

B.6 SNC vs. Y14 Data

We have thus far made use of Y14 filings as the primary data source in the paper. Y14 has the advantage of recording a number of loan characteristics that are of use to us. However, as a tool for stress testing, it is inherently a data set focused on the largest banks. An alternative data set, which records loan characteristics and includes smaller banks, is the Syndicated National Credit (SNC) registry. This data set tracks all syndicated loans held by at least two (now three) banking entities with a total size of 20 (now 100) million USD (changes occurred in 2018). Unfortunately, the SNC data has some short comings that make it less useful than the Y14 as a baseline data set. It is inherently focused on larger syndicated loans, which are a specific subset of all loans[32]. Perhaps more importantly, the SNC data does not include information on rates paid, which is a key variable in our analyses on information based loan pricing.

Nevertheless, the fact that we are able to make use of a larger set of banks as well as the fact that we are able to make use of a longer data series make the SNC registry useful as a tool for confirming our above findings. In order to obtain rates paid for loans, we merge SNC data with Dealscan data. We follow

[31] This follows earlier work on specialization such as Gopal (2021).

[32] The specialization of the arranging entity may be less relevant in cases where hundreds of loan participants influence loan term flexing.

the fuzzy matching approach laid out by Cohen, Friedrichs, Gupta, Hayes, Lee, Marsh, Mislang, Shaton, and Sicilian (2018), based on the borrower name and common loan variables. We keep all loans originated between 2000 and 2019 in order to obtain a consistent sample. We remove loans that have performance issues by the time they are first observed in the data and all loans that are originated more than a year before they are observed, as we are interested in new loans only. We include each loan only once – to avoid counting the large term B loans hundreds of times – and make use of the specialization of the arranging entity. Our sample comprises just over 11,000 loans for which we have rate data and just over 30,000 loans for which we have performance data. These loans are originated by 218 different banks (measured at the level of the high-holder). Though still large entities, many of these are smaller than the banks covered by the Y14.

In Table B.6 we show that the rates paid by borrowers for syndicated loans arranged by more specialized banks are lower, on average. The difference is not always significant if we include a full set of detailed controls (see column (3)). In this case, including arranger*time fixed effects absorbs a lot of variation given the outsized role a few arrangers play in our data and the fact that our key variable varies at the arranger*time level. Even so, the coefficient remains strongly negative. Moreover, we can see from Figure B.1 that the rate differential is always negative, even if it is insignificant at times. Moreover, the figure reveals that the crisis period of 2008-2010 does not change our results. In fact, borrowers are more likely to pay lower rates to specialized lenders during this time period. In columns (4)-(6) of Table B.6 we further show that the performance of loans made by specialized lenders is always somewhat better than the performance of loans made by less specialized lenders. This difference is small, but nonetheless noteworthy given the small average default rate of loans in the SNC sample (<4%). It is noteworthy that the magnitude of our coefficients in SNC analyses are highly similar to those in our baseline Y14 regressions, discussed above.

B.7 Multiple Specialized Lenders in One Industry

We have studied the interaction between specialization and whether the industry has multiple specialized lenders, aiming to rule out the alternative hypothesis that negative interest wedge is driven purely by competition among specialized lenders within one industry. In the baseline we define an industry to have "Multiple Specialized Lenders" if two or more banks specialize in it.

Table B.7 lists the number of banks that are specialized in industries in our data, where we have obscured the exact industry definition in favor of stylized industry names in Table B.7, though each represents a two-digit industry (with the omission of finance and insurance). As shown in Table B.7, the number of banks that are specialized in industries varies greatly. Some industries are home to no specialized banks, while other industries see nine banks that are specialized.

Recognizing the great variation of the number of specialized lenders across industries, we introduce additional tests to show that our results discussed above (wherein we interact our variable of interest with a dummy for lender multiplicity) are robust to alternative definition of the multiplicity of specialized lenders. In Table B.8 we take the number of banks in an industry directly, and show that interacting bank specialization with this continuous measure does not change our baseline results.

Table B.1: **Summary Statistics of Key Variables**

	N	Mean	SD	Specialized	Non-Specialized	Differential
Interest Rate	353,544	3.69	1.64	3.55	3.69	-0.13***
Non-Performing	353,544	0.04	0.19	0.03	0.04	-0.01***
Loan Amount	353,544	12.42	5.43	10.5	12.99	2.5***

Note: This table shows summary statistics for loans in our sample. We count each bank-loan combination only once, on the date when it is first observed in our data (this may be a different date from the loan's first origination date for a small subset of loans only as we censor our data and start in 2012, one year after collection began in 2011). Loan size is scaled by 1 million USD. The interest rate is the unadjusted cost of the loan, measured in percent."Non performing" is a dummy that takes the value of 1 if the loan ever falls in arrears, has negative maturity or is otherwise in default after the first observation in our sample. The mean values of each variable data are split by whether a loan is made by a specialized bank or not.

Table B.2: **Summary Statistics for Rating Categories**

Rating Group	Debt/EBITDA	Return on Assets	Leverage (Assets to Borrowing)
1	2.9	0.111	3.16
2	3.31	0.109	3.59
3	3.92	0.055	4.26

Note: For around (50%) of firms in our data that report EBITDA, ROA, or leverage information, we show how Debt/EBITDA, RoA, and Leverage relate to our three risk categories ("high risk", "mid-risk", and "low risk" – abbreviated as 1-3) in our data.

Table B.3: **Interest Rate and Loan Performance – Alternative Risk Definition**

Panel A – Continuous Rating and Rate

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank	-0.070***	-0.150***	-0.083***	-0.008***	-0.006***	-0.005***
	[0.005]	[0.006]	[0.006]	[0.001]	[0.001]	[0.001]
Log loan amount	-0.158***	-0.169***	-0.176***	-0.000	0.000	-0.000
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Interest rate				0.013***	0.014***	0.014***
				[0.000]	[0.000]	[0.000]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating FE	X	X	X			
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	353,544	353,544	353,544	353,544	353,544	353,544

Panel B – Borrower Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank	0.053	-0.093***	-0.049***	-0.008***	-0.009***	-0.004***
	[0.037]	[0.009]	[0.010]	[0.001]	[0.001]	[0.001]
Log loan amount	-0.201***	-0.206***	-0.204***	-0.003***	-0.003***	-0.003***
	[0.003]	[0.003]	[0.003]	[0.000]	[0.000]	[0.000]
Borrower leverage	0.006**	0.007**	0.007**	0.006***	0.005***	0.005***
	[0.003]	[0.003]	[0.003]	[0.000]	[0.000]	[0.000]
EBIT to ST-Debt	-0.016***	-0.019***	-0.017***	-0.006***	-0.006***	-0.006***
	[0.003]	[0.003]	[0.003]	[0.000]	[0.000]	[0.000]
EBIT to LT-Debt	0.015***	0.024***	0.021***	0.002***	0.002***	0.002***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.34	0.43	0.45	0.0091	0.025	0.031
N	175,842	175,840	175,534	175,842	175,840	175,534

Note: In Columns (1) – (3), we regress the loan rate paid by a given firm on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. We make use of rating dummies (high risk, medium risk, low risk) in columns (1)-(3) and interest rate in columns (4)-(6) as risk controls. Panel B replicates Panel A. It makes use of firm leverage (debt to assets) and short term as well as long term debt to EBIT as measures of borrower riskiness as opposed to loan interest rates or bank risk ratings. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table B.4: **Interest Rate and Loan Performance – 4 Digit Industry**

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank (4 Digit)	-0.071***	-0.242***	-0.189***	-0.012***	-0.006***	-0.007***
	[0.007]	[0.008]	[0.008]	[0.001]	[0.001]	[0.001]
Log loan amount	-0.158***	-0.169***	-0.175***	-0.000	-0.000*	-0.001**
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating Category (1-3) FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	353,544	353,544	353,544	353,544	353,544	353,544

Note: In Columns (1) – (3), we regress the loan rate paid by a firm on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 1% or more in an industry, relative to what would be expected from diversification. Variables are defined at the 4-digit NAICS level. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table B.5: **Interest Rate and Loan Performance – Excluding COVID Period**

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank	-0.082***	-0.156***	-0.085***	-0.007***	-0.005***	-0.005***
	[0.006]	[0.006]	[0.007]	[0.001]	[0.001]	[0.001]
Log loan amount	-0.165***	-0.174***	-0.181***	-0.001**	-0.001*	-0.001**
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating Category (1-3) FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	302,312	302,312	302,312	302,312	302,312	302,312

Note: In Columns (1) – (3), we regress the loan rate paid by a firm on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. We exclude loans originated in 2020 or 2021, as these are denoted as "abnormal COVID periods". Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table B.6: **Interest Rate and Loan Performance – SNC Data**

	(1)	(2)	(3)	(4)	(5)	(6)
		Allindrawn Spread			Non-Performing Loans	
Specialized Bank	-0.109**	-0.104*	-0.031	-0.006**	-0.009**	-0.009**
	[5.436]	[4.731]	[7.597]	[0.003]	[0.004]	[0.004]
Loan amount	-0.013***	-0.013***	-0.012***	0.000	0.000	0.000
	[0.001]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating FE	X	X	X	X	X	X
Bank-Year FE			X			X
Industry-Year FE		X	X		X	X
R^2	0.61	0.69	0.71	0.24	0.33	0.36
N	11,460	11,460	11,460	32,391	32,391	32,391

Note: In Columns (1) – (3), we regress the allindrawn spread (from Dealscan) on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates (i.e. whether the lead arranger in a syndicate is over-invested in the banks industry). We define a bank as specialized if it is over-invested by 3.5% or more in an industry, relative to what would be expected from diversification. This corresponds to being among the top 20% of lenders by over-investment at a given point in time. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

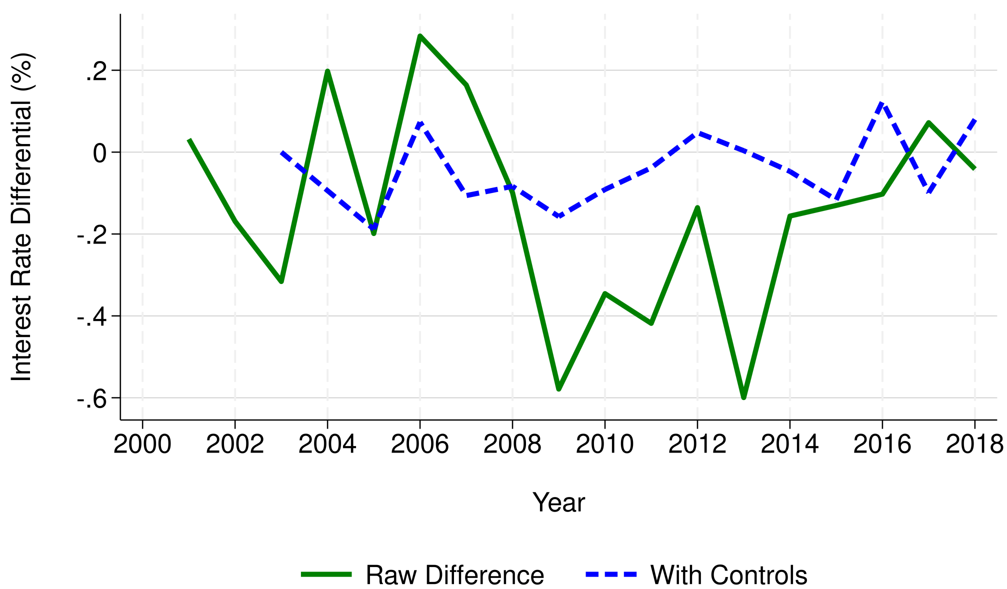

Figure B.1: **Rates in SNC Data** This Figure shows the difference in interest rates paid by borrowers for loans arranged by specialized vs. unspecialized banks in SNC data over time. We define specialized lenders as those with more than 3.5% over-investment in an industry, where over-investment is measured as deviations from a diversified portfolio $\frac{LoanAmount_{b,i,t}}{\sum_s LoanAmount_{b,i,t}} - \frac{LoanAmount_{i,t}}{\sum_i LoanAmount_{i,t}}$ for bank b in industry i at time t. We make use of loans from SNC that have been merged with Dealscan as described in Cohen, Friedrichs, Gupta, Hayes, Lee, Marsh, Mislang, Shaton, and Sicilian (2018). The green line does not account for loan characteristics while the blue line accounts for origination date, purpose, loan type, loan riskiness and agent fixed effects.

Table B.7: **Number of Banks Specialized per Industry**

Industry	Number of Specialized Banks
A	0
B	1
C	3
D	0
E	2
F	2
G	4
H	3
I	7
J	0
K	2
L	0
M	3
N	9
O	2
P	1
Q	0
R	3
S	9
T	1
U	4
V	3
W	5

Note: We indicate the number of banks specialized in stylized industries. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification (i.e. a bank that invests 14% of its C&I portfolio in an industry that accounts for 10% of all C&I lending would be specialized in that industry.) An industry is competitive if 2 or more banks are specialized in it.

Table B.8: **Interest Rate and Loan Performance – Alt. Def. of Multi-Specialized-Lenders**

	(1)	(2)	(3)	(4)	(5)	(6)
		Interest Rate			Non-Performing Loans	
Specialized Bank	-0.240***	-0.245***	-0.084***	-0.010***	-0.005**	-0.008***
	[0.012]	[0.013]	[0.014]	[0.002]	[0.002]	[0.002]
Specialized Banks in Ind. × Specialized	0.038***	0.021***	0.000	0.000	0.000	0.001
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Log loan amount	-0.157***	-0.171***	-0.176***	-0.000	-0.000	-0.001**
	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]
Specialized Banks in Ind.	-0.020***	-0.012***	0.000	-0.001***	-0.001***	0.000
	[0.001]	[0.001]	[.]	[0.000]	[0.000]	[.]
Year-Quarter FE	X	X	X	X	X	X
Purpose FE	X	X	X	X	X	X
Rating Category (1-3) FE	X	X	X	X	X	X
Bank-Year FE		X	X		X	X
Industry-Year FE			X			X
R^2	0.31	0.39	0.4	0.031	0.044	0.047
N	353,544	353,537	351,776	353,544	353,537	351,776

Note: In Columns (1) – (3), we regress the loan rate paid by a firm on the fixed effects specified at the bottom of the table and a dummy denoting whether the firm is borrowing from a bank that is specialized in the industry in which said firm operates. We define a bank as specialized if it is over-invested by 4% or more in an industry, relative to what would be expected from diversification. We interact the dummy of "Specialization" with the number of specialized banks in the industry in question. In Columns (4) – (6), we use the same specifications as in previous columns, but make use of whether the loan in question ever becomes non-performing at any date it is in our sample after its origination. A loan becomes non-performing if it is ever in arrears, has not been paid down at maturity, or defaults outright. We interact our variable of interest with the number of banks that are considered "specialized" in an industry. Standard errors are clustered at the firm-time level and are heteroskedasticity robust while *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.