Bigtech Credit Market Competition and Bank Portfolio Risk*

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Abstract

How does bank lending reacts when BigTech platforms use their proprietary information to compete for their borrowers? To explore this, I develop a model of the credit market where I show that platform entry, by attracting comparatively more safe borrowers, can increase the bank's portfolio risk. Improvements in platform information strengthen this adverse selection problem, while funding costs shape the extent of competition. Despite deteriorating bank portfolio quality, platform entry can expand productive lending and improve aggregate efficiency. These findings highlight how information-driven competition can have contrasting effects on incumbent banks and aggregate credit allocation.

Keywords: Banking, Credit Market Competition, Digital Platforms

JEL Codes: G21, G23, L1

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1 Introduction

The growing dominance of digital platforms and BigTech firms across various sectors has raised significant concerns regarding their impact on competition. These firms leverage their vast stocks of user data, cutting-edge technologies, and network effects to expand into markets historically served by regulated incumbents, one of them being the financial sector.

Unlike conventional financial intermediaries, BigTech platforms accumulate data from interactions within their digital ecosystems, including e-commerce transactions, payments, and other online activities. These data can provide valuable information about borrowers' creditworthiness, allowing platforms to enter lending markets without relying exclusively on traditional credit histories or costly borrower screening. Moreover, as digital ecosystems expand, the information generated by their users can become increasingly valuable through economies of scale and data externalities (Frost et al., 2019; Boissay et al., 2021; Bergemann et al., 2022). The resulting informational advantages raise important questions about how platform entry changes competition with incumbent banks and the allocation of credit across lenders.

This paper asks how a data-rich platform's entry affects an incumbent bank's lending decisions and portfolio risk. The key difficulty is that the bank does not passively accept the entrant's selection of borrowers. It can change its lending rate and invest in screening, while borrowers select lenders according to both loan terms and the relative convenience, or preference, for each of them.

To formalize this situation, I develop a model of the credit market with an incumbent bank and a potential BigTech lender. Borrowers differ in their repayment probabilities and in their relative preferences for traditional and digital lending. This last dimension can be thought of as a relative location to each lender. Furthermore, I assume the bank can serve the entire population and chooses a costly screening intensity and a common loan rate. The platform is restricted to lending only to previous users of its ecosystem and relies on information generated by their earlier non-financial activities. Crucially, platform adoption

plays two roles. It determines how many borrowers the entrant can reach, but also how precisely the platform can assess their creditworthiness. Platform previous adoption in the model is taken as given, allowing the analysis to isolate the effects of an existing digital ecosystem on subsequent credit-market competition. The key distinction of our model is that the platform's informational advantage is tied to an existing non-financial customer base. This means, it need not be more accurate than the bank's signal at every adoption level. Its expansion changes the number of loans exposed to competition and the quality of the information used to compete for them. This joint movement is what distinguishes platform penetration from the entry of a lender with fixed informational capabilities.

The first result identifies a selection mechanism that can make the bank's retained portfolio riskier. In the model, platform entry increases the bank's expected default frequency precisely when it displaces a larger proportion of safe than risky bank loans. In the benchmark competition region, safe borrowers can receive competing acceptable offers, whereas risky borrowers do not have the same overlap. The platform consequently draws away profitable safe loans without directly displacing risky bank lending. The resulting deterioration in portfolio quality need not reflect greater risk-taking by the bank. It can arise even when the volume of risky bank loans is unchanged.

The bank's endogenous response does not necessarily reverse this effect. In the interior benchmark region, its optimal common rate, conditional on screening, is higher than under bank-only lending. Although cutting the rate could recover some borrowers from the platform, the discount would also apply to loans the bank would otherwise retain and could attract additional risky applicants. The bank therefore trades off defending a marginal borrower against repricing its existing lending business. Its screening response is comparatively modest in the numerical benchmark. Entry reduces the return to identifying safe borrowers because some choose the platform, but screening remains valuable for avoiding loss-making risky loans; the platform's pricing response further influences this trade-off. Thus, portfolio deterioration is driven principally by borrower reallocation rather than by a large reduction

in bank screening.

The model's comparative statics distinguish the platform's market reach from the quality of its information. At a given adoption level and unchanged lending decisions, a more precise platform signal raises the bank's expected default frequency when both types are funded and some loans are contested, while reducing its gross return to screening. The entrant more effectively identifies safe borrowers, lowering the value to the bank of acquiring information about customers it may not retain. Funding costs operate through a different margin. By changing lending profitability and the overlap of acceptable offers, they can alter which borrowers are directly contested and, consequently, the bank's equilibrium pricing and screening responses. The informational selection effect is therefore distinct from adjustments driven by market coverage.

A further contribution is to show that deteriorating bank portfolio quality need not imply a less efficient allocation of credit. Platform entry can finance safe projects that would remain unfunded under bank-only lending, but it also diverts some loans toward an intermediary with higher funding costs. In the numerical benchmark, productive surplus initially falls below the bank-only outcome before exceeding it as adoption expands. A higher expected default frequency in the bank's retained portfolio can therefore coexist with greater aggregate productive efficiency. Evaluating platform competition through incumbent default rates alone would overlook this distinction.

The model also offers a set of testable implications that go beyond changes in lending volumes. Borrowers first select into applications, lenders screen imperfectly, and approved borrowers may choose a competing offer. Neither a contraction in bank lending nor an increase in its default frequency, by itself, identifies the selection mechanism. The relevant evidence would then need to compare the credit quality of applicants and originated loans, and assess whether platform penetration disproportionately displaces safe bank lending where ecosystem information is more predictive of repayment risk.

Section 2 positions the contribution within the related literature, and Sections 3–4 intro-

duce the model and the bank-only benchmark. Section 5 establishes the portfolio-selection and pricing results under platform competition. Section 6 examines platform information and funding-cost effects, Section 7 examines productive efficiency and welfare, and Section 8 concludes.

2 Related literature

Information acquisition and credit-market competition. Our paper relates to the literature examining how lender information affects pricing, credit allocation, and the incentives to acquire information. Within this strand, Broecker (1990) studies competition with imperfect creditworthiness tests, while Marquez (2002) shows how the distribution of borrower information across banks shapes adverse selection and loan pricing. Hauswald and Marquez (2003) distinguish better information processing from easier access to rivals' information, and Hauswald and Marquez (2006) analyze the strategic value of proprietary information acquisition. We retain the bank's incentive to invest in screening, but introduce a competitor (a BigTech company) whose information is produced outside lending relationships. This may give the entrant an informational edge when compared to the bank. As a consequence, the bank's portfolio can become riskier because the entrant disproportionately takes away safe customers.

Related work studies differences in lenders' technologies. Vives and Ye (2025a) examine information technology, competition, investment, and welfare with borrower moral hazard, while Vives and Ye (2025b) analyze FinTech entry when lenders differ in monitoring efficiency, funding costs, and pricing flexibility. He et al. (2024) distinguish the breadth of hard information from its precision. Our focus is instead on the role of competing screening technologies used to infer borrowers' types when platform adoption simultaneously expands the entrant's potential clientele and improves its credit signal. Because the bank chooses screening and a common rate anticipating the platform's response, we can identify why defending

marginal borrowers need not reduce the incumbent's rate and why its screening incentives can remain strong even as profitable loans are diverted.

Data externalities and information from digital ecosystems. Bergemann et al. (2022) show how information about one consumer can reveal information about others, creating data externalities. Parlour et al. (2022) examine how competition for payment flows changes the credit information generated within bank relationships, and Chiu and Koeppl (2026) study the interaction between platform data and payment services. We take the platform's ecosystem and its adoption base as given rather than modeling data acquisition, sharing, or monetization. This allows us to isolate the impact of data externalities in credit markets. A larger user base raises the platform's screening precision at the same time as it exposes more borrowers to competing offers, eroding the bank's returns from identifying safe applicants even though no information is transferred between lenders.

Platform lending and credit allocation. A third strand studies the distinctive mechanisms through which platforms provide credit. Li and Pegoraro (2026) emphasize repayment enforcement through access to e-commerce, and Gambacorta et al. (2023) study the interaction of marketplace lending with fees and investment incentives. Biancini and Verdier (2023) show that competition with a two-sided lending platform can change the quality of borrowers served by banks and need not reduce repayments, through the participation of borrowers and investors. Liu et al. (2022) document differences between BigTech and bank business loans in their terms and borrower characteristics. We abstract from ecosystem enforcement, marketplace cross-subsidies, and investor matching to isolate the consequences of an entrant's proprietary credit signal. Our results connect the pricing and borrower-selection effects of platform entry to an explicit prediction for the incumbent's loan portfolio. Moreover, the loss of safe bank originations can coexist with additional safe lending and higher aggregate productive surplus, so bank portfolio risk and economy-wide credit allocation need not move together.

3 Model

Consider an economy with a unit mass of risk-neutral households, an incumbent bank, and a BigTech platform that may enter the credit market. Each household has a productive project requiring one unit of external financing and can borrow from at most one intermediary, which we denote by $\ell \in \{b, p\}$. For the model we will use the subscripts b and p to refer to the bank and the platform, respectively. Households differ in their privately observed creditworthiness and in the convenience they derive from borrowing through either lending channel (also referred as their relative location from each lender). The intermediaries know the distribution of these characteristics, but not their individual realizations.

The two lenders differ in both market access and information acquisition. The bank can serve the entire population and invests in screening to improve its assessment of borrowers' repayment probabilities. On the other hand, the platform can offer credit only to households that have previously used its non-financial services. Its assessment of credit risk relies instead on information generated within that ecosystem, whose informativeness improves as the user base expands. Both lenders use imperfect signals to decide which applicants to approve, and each offers a common interest rate to its approved borrowers. Conditional on receiving credit offers, households compare the rates and the convenience of either lender, while they may also decline financing.

These features create distinct margins of borrower selection. Borrowers first apply according to their credit type and the lending terms they would accept. Screening then determines who receives an offer, and borrowers receiving two acceptable offers choose their preferred intermediary. Acting as the incumbent leader, the bank chooses its screening and lending terms anticipating the platform's response and the composition of its eventual loan portfolio.

3.1 Timing

The sequence of decisions is illustrated in Figure 1. At the beginning of the game, households learn their credit types and relative lender preferences. The bank then commits to a screening intensity I, a common interest rate R_b, and a signal-contingent approval policy $\mathcal{M}_b$. After observing this commitment, the platform decides whether to enter and, if so, chooses a common rate R_p and an approval policy $\mathcal{M}_p$. The bank knows the aggregate extent of platform adoption but not individual adoption status, whereas the platform observes which households belong to its ecosystem.

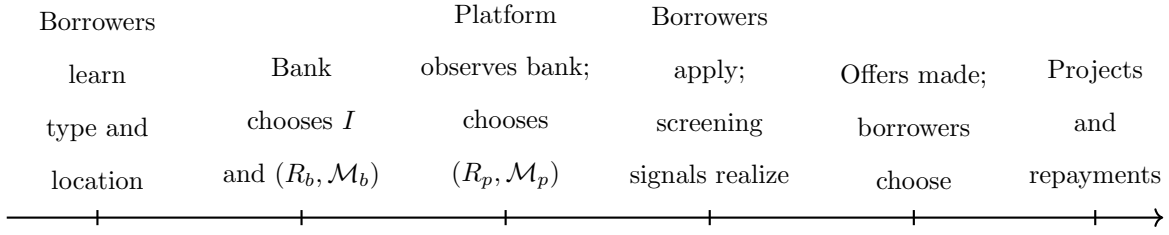


Figure 1: Timing of the sequential bank–platform lending game.

Applications take place after the rates are announced, but before the screening signals are realized. Lenders subsequently implement their committed approval policies, and borrowers choose among the offers they receive. Projects are then realized and successful borrowers repay their lenders. In particular, rates and approval policies cannot be revised in response to the realized signals or to an applicant's privately observed lender preference.

3.2 Households

We assume that an exogenous share $\mu \in [0, 1]$ of households previously adopted the platform through non-financial activities, such as using its marketplace or digital services. The bank may lend to all households, whereas the platform's existing user base determines which households it can approach with credit. We formalize this restriction as follows:

Assumption 1 (Exogenous Market Segmentation)**.** *The Bigtech platform can only lend to households that have previously adopted the platform*

This creates a captive segment for the bank. However, given our assumptions the bank cannot observe if a borrower belongs to this group. This would be equivalent to prevent the bank from offering different rates based on adoption status of the platform's ecosystem.

Households are heterogeneous in creditworthiness, which directly impact how likely are they to repay a loan. We assume that the distribution of credit types is binary. For $j \in \{S, R\}$, the probability of project success is

$$\theta^j = \begin{cases} \theta^S & \text{with probability } p, \\ \theta^R & \text{with probability } 1-p. \end{cases}$$

We refer to households with $\theta^j = \theta^S$ as safe types and households with $\theta^j = \theta^R$ as risky types. We assume $\theta^S > \theta^R$, so that safe borrowers have a higher probability of repaying their loans. These labels refer to relative riskiness, since both credit types can experience project failure.

The project's realized output is contingent on the credit type. In particular, we define the output of a financed project as:

$$V^j(\theta^j) = \begin{cases} \dfrac{Y^j}{\theta^j} & \text{with probability } \theta^j, \\ 0 & \text{with probability } 1-\theta^j. \end{cases}$$

This specification allows expected project returns to differ across credit types, even though safe types have a higher probability of success. Risky projects could, for instance, have higher output conditional on success. Notice that expected output for a type-j project is Y^j. Throughout the analysis we impose the following restriction on the expected returns from risky lending:

Assumption 2. *Calling c_ℓ the unit cost of lending for each lender, we will have that a funded true risky project has negative net present value for both lenders, such that:*

$$Y^R - c_\ell < 0 \qquad \textit{for } \ell = \{b, p\}.$$

This does not mean that a true risky borrower will never receive funding or that it is not profitable for her to do so. A risky borrower might get funding if she is misclassified as safe by either intermediary, or if a particular lender finds it profitable to offer a contract under either signal.

In addition to their credit type, borrowers differ in the convenience of using the two lending channels. Following the spatial approach to banking competition (Vives and Ye, 2025a), the bank and the platform are located at opposite endpoints of a unit interval. At the same time as observing their credit type, each household privately observes their relative lender preference, or location, $x_i \sim U[0, 1]$. Particularly, for the households, bank financing entails a nonpecuniary cost tx_i, whereas the preference for platform financing is symmetric and given by $t(1 - x_i)$. Here, the parameter $t > 0$ captures the importance of lender differentiation. These costs are incurred only when a loan is obtained. As mentioned before, the outside option for every borrower is normalized to zero.

Importantly, the credit-type, the location and adoption status (whether the borrower has adopted the platform's ecosystem previously or not), are mutually independent. This highlights the fact that household originally adopted the platform because of some convenience or utility that was unrelated to the credit market. However, the relative preference given by x_i is directly related to the convenience of the originated loan. Some people might still use the original product of a digital platform or a Bigtech company, but may be wary of funding themselves through it because some personal preference.

3.3 Borrower choice and conditional demand

Each lender posts a common repayment R_b or R_p, due only after success. We refer to these repayments as interest rates. A type-j borrower receiving a bank offer obtains expected utility

$$u_b^j = Y^j - \theta^j R_b - t x_i. \tag{3.1}$$

A platform adopter receiving a platform offer obtains instead

$$u_p^j = Y^j - \theta^j R_p - t(1 - x_i). \tag{3.2}$$

Not borrowing yields zero utility. The first object we need is the set of borrowers who would be willing to accept a loan from a given lender if that were the only available offer. For the bank, a type-j borrower accepts if and only if expected utility is nonnegative, that is,

$$u_b^j \geq 0 \iff x_i \leq \bar{x}_b^j \equiv \frac{Y^j - \theta^j R_b}{t}. \tag{3.3}$$

The cutoff $\bar{x}_b^j$ is the marginal type willing to borrow from the bank. Borrowers located to the left of this cutoff accept a bank loan if approved, while those to the right prefer not to borrow when the bank is the only option. A higher bank rate lowers $\bar{x}_b^j$, shrinking the bank's potential market.

For the platform, an adopting type-j borrower accepts if and only if

$$u_p^j \geq 0 \iff x_i \geq \bar{x}_p^j \equiv 1 - \frac{Y^j - \theta^j R_p}{t}. \tag{3.4}$$

Hence $\bar{x}_p^j$ is the marginal adopter willing to use platform credit. Borrowers to the right of this cutoff accept the platform loan if approved. A higher platform rate raises the threshold and contracts the set of adopters willing to borrow.

When both lenders make acceptable offers, the relevant margin is no longer participation

but lender choice. A type-j borrower weakly prefers the bank if and only if

$$u_b^j \geq u_p^j \iff x_i \leq \bar{x}^j \equiv \frac{1}{2} + \frac{\theta^j(R_p - R_b)}{2t}. \tag{3.5}$$

The cutoff $\bar{x}^j$ therefore separates borrowers who prefer the bank from those who prefer the platform when both loans are available. Because expected repayment depends on credit type, the same difference in posted rates can induce different lender choices for safe and risky borrowers.

To express conditional demand, let D_ℓ^j be the share of type-j borrowers who would accept a loan from lender ℓ if it were the only available offer. For interior participation thresholds, these demands are

$$D_b^j = \bar{x}_b^j, \tag{3.6}$$

for the bank, and

$$D_p^j = 1 - \bar{x}_p^j, \tag{3.7}$$

for the platform. Since applications are costless and screening outcomes are not yet known, these same objects determine the composition of each lender's applicant pool.

A concept that will be used repeatedly below is the *contestable segment*. A platform adopter is contestable when she would accept credit from either lender if both offers are available. For type-j borrowers, the interval of contestable locations is bounded by $\bar{x}_p^j$ and $\bar{x}_b^j$ when these cutoffs overlap. We distinguish this overlap from the broader set of previous adopters whom the platform can approach.

Definition 1 (Market coverage)**.** *Conditional on both intermediaries extending loan offers, the market is covered for borrowers of type j whenever every realization of their relative lender preference admits at least one contract yielding nonnegative expected utility.*

Figure 2 illustrates the interior covered-market case, in which $0 < \bar{x}_p^j < \bar{x}^j < \bar{x}_b^j < 1$. Every borrower has at least one acceptable offer in this region, and some borrowers would

accept either one.

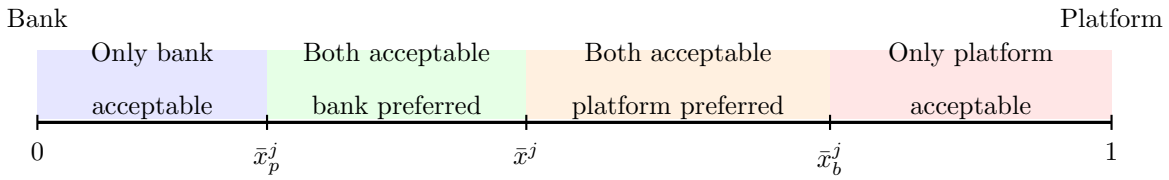


Figure 2: Borrower choice in the interior covered-market case. The shaded regions correspond to the participation and choice intervals implied by the cutoffs.

Let $\widetilde{D}_\ell^j$ denote the share of type-j borrowers who choose lender ℓ when both lenders make acceptable offers. In the covered case,

$$\widetilde{D}_b^j = \bar{x}^j, \qquad \widetilde{D}_p^j = 1 - \bar{x}^j. \tag{3.8}$$

These expressions make the role of the cutoffs transparent. The one-offer cutoffs, $\bar{x}_b^j$ and $\bar{x}_p^j$, describe participation, while $\bar{x}^j$ describes the allocation of contestable borrowers across lenders. The difference $D_b^j - \widetilde{D}_b^j$ therefore measures the share of bank borrowers that may be displaced once the platform is also active. Appendix B.6 presents the more general demand expressions for uncovered markets and for cases in which the cutoffs lie outside the unit interval.

Market coverage does not imply that every applicant receives credit, since offers remain conditional on screening. The benchmark equilibrium below features overlapping acceptable offers for safe borrowers but not for risky borrowers. Hence, the covered-market demand expressions apply directly to safe types. For risky types, a competing offer does not displace the bank's demand, so $\widetilde{D}_b^R = D_b^R$. Keeping these cases distinct is essential for the portfolio-selection mechanism in Section 5.

3.4 Bank

The bank obtains funds at constant unit cost c_b and offers the same interest rate R_b to all approved applicants. It chooses screening intensity $I \in [0, 1)$ at cost

$$C(I) = \kappa \frac{I^2}{1 - I}, \qquad \kappa > 0. \tag{3.9}$$

The cost is increasing and convex, so higher screening effort is progressively more expensive and perfect information is prohibitively costly.

The bank's information about borrowers is built in two phases. The first one comes from *selection into applications*. Since households apply only when bank credit would be acceptable if approved, the composition of the bank's applicant pool already depends on the posted rate through the type-specific demands introduced above. We summarize this first stage by the safe-type share among bank applicants,

$$p_b(R_b) = \frac{pD_b^S(R_b)}{pD_b^S(R_b) + (1-p)D_b^R(R_b)}. \tag{3.10}$$

This prior need not coincide with the population share p. Even though credit type and location are independent, safe and risky borrowers can differ in their willingness to apply at a given interest rate. The bank therefore starts from an applicant pool that may already be positively or negatively selected.

Afterwards, the beliefs of the bank about a borrower's credit type would be updated again, following the result from the screening signal itself. Let $m \in \{s, r\}$ denote the resulting bank's signal, where s is a safe-type signal and r means that the technology delivered a signal telling the bank the applicant is of the risky type. Signal accuracy is symmetric across true credit types, such that $\Pr(m = s \mid j = S) = \Pr(m = r \mid j = R) = \gamma(I)$. Following Hauswald and Marquez (2003) we make the precision of the signal to be increasing in the effort put

into operating the screening technology:

$$\gamma(I) = \frac{1+I}{2}. \tag{3.11}$$

This is the precision of the screening signal used to update the *interim* prior p_b using Bayes' rule. Thus, the bank's posterior assessment of creditworthiness consequently depends on both the composition of applicants and the accuracy of screening. Appendix A.1 provides the corresponding posterior expressions.

The bank commits to one approval set $\mathcal{M}_b \subseteq \{s, r\}$ before signals are realized and extends a loan to an applicant if her signal is in that set. In the benchmark equilibrium, $\mathcal{M}_b = \{s\}$, meaning that the bank approves borrowers with safe signals only. Because the bank offers a common rate, it cannot separately tailor the contract for infra-marginal borrowers and for borrowers contested by the platform. This common-rate restriction is central for the pricing results that follow.

Even after the bank approves an applicant, origination is not guaranteed. An approved borrower may still choose the platform if both lenders extend acceptable offers. The bank therefore internalizes not only who applies and how precisely it can screen them, but also how many approved borrowers it ultimately retains.

3.5 The BigTech platform

The platform's unit funding cost is $c_p = \psi c_b$, with $\psi > 1$ in the benchmark. Thus, we assume the incumbent bank has a funding advantage. This is related to banks typically having access to relatively cheaper, and more stable, sources of funding, such as deposits. The platform, contrary to the bank, evaluates prospective borrowers using ecosystem data. The platform posts a rate R_p and chooses an approval set $\mathcal{M}_p \subseteq \{s, r\}$, where $\mathcal{M}_p = \varnothing$ means no lending.

As with the bank, the platform's information is shaped in two phases or stages. First,

there is selection into applications. Conditional on having adopted the platform, the probability that an applicant is safe is

$$p_p(R_p) = \frac{pD_p^S(R_p)}{pD_p^S(R_p) + (1-p)D_p^R(R_p)}. \tag{3.12}$$

Because adoption is independent of creditworthiness and relative preferences for a lender, the common factor μ cancels out in this conditional prior. Nevertheless, p_p depends on the platform's posted rate because safe and risky adopters need not be equally willing to apply. The platform may therefore face a different applicant pool from the bank even before either lender screens borrowers.

Second, the platform receives a binary screening signal $n \in \{s, r\}$. Its accuracy is again symmetric across true credit types and its precision depends on ecosystem adoption and the effectiveness of data processing. We assume then that how accurate the screening signal of the platform is depends primarily on the mass of previous adopters of its ecosystem in the following way:

$$\delta(\mu; \alpha) = \frac{1 + \mu^{1/\alpha}}{2}, \qquad \alpha \geq 1. \tag{3.13}$$

Hence $\Pr(n = s \mid j = S) = \Pr(n = r \mid j = R) = \delta(\mu; \alpha)$. When $\alpha > 1$, the platform's signal becomes more informative with adoption at a diminishing rate, and a larger α raises precision for any interior adoption level. This technology captures, in a reduced form, the idea that a larger ecosystem generates data that improve the platform's assessment of borrowers. Not only that, but a higher α is related to the fact that the data generated by an user of the platform not only helps in inferring something about him, but also helps to predict the type or characteristics (in this case, their credit type) of other users. In a nutshell, this is how the idea of *data externalities* (Bergemann et al., 2022) enters into the model.

Once the signal is realized, the platform updates its applicant-pool prior p_p using Bayes' rule. Its posterior assessment of creditworthiness depends on the composition of applicants and the precision of its data-based signal. The corresponding posterior expressions are

provided in Appendix B.3.

Because the lenders' signals are private and conditionally independent given borrower type, screening by one intermediary does not directly improve the other's signal. Nevertheless, screening generates an allocation externality. Approval by one lender affects the probability that the other originates a loan, while borrowers receiving two offers choose their preferred contract. Imperfect screening can therefore change the risk composition of the rival's retained portfolio without direct information sharing. This effect is distinct from the data externality captured by $\delta(\mu;\alpha)$, through which broader ecosystem adoption improves the platform's signal precision.

4 Benchmark with only bank lending

We first consider an economy in which the bank is the only lender. This benchmark establishes how its common interest rate and costly screening determine the allocation and risk composition of credit before the platform enters. The bank chooses $(R_b, I, \mathcal{M}_b)$ to maximize expected profits. We focus on lending after favorable screening signals, $\mathcal{M}_b = \{s\}$, which is optimal in the benchmark calibration. Appendix A.4 compares alternative lending policies, while Appendix A.5 considers participation boundaries.

4.1 Monopoly pricing and screening

Under favorable-signal lending, the bank finances a safe applicant with probability $\gamma(I)$ and a risky applicant with probability $1-\gamma(I)$. Since applications depend on the posted rate, the masses of originated loans to each true type of borrower are:

$$L_0^S = pD_b^S\gamma(I), \qquad L_0^R = (1-p)D_b^R[1-\gamma(I)]. \tag{4.1}$$

These masses reflect both selection into applications as well as screening. Define $m_b^j \equiv \theta^j R_b - c_b$ as the expected margin on a type-j loan. Then, we can write the bank's expected

profit as:

$$\Pi_b^M(R_b, I) = L_0^S m_b^S + L_0^R m_b^R - C(I). \tag{4.2}$$

By Assumption 2, a risky loan that the borrower is willing to accept has a negative expected margin. More precise screening therefore allows the bank both to identify profitable safe applicants and to avoid losses from financing risky ones.

The bank's interest rate trades off the expected repayment on each loan against the number of borrowers willing to apply. Because the bank posts a common rate, this trade-off takes into account both credit types. For a given screening intensity and interior participation thresholds, expected profit is strictly concave in R_b, with conditional optimum

$$R_b^M(I) = \frac{p\gamma(I)\theta^S(Y^S + c_b) + (1-p)[1-\gamma(I)]\theta^R(Y^R + c_b)}{2\big[p\gamma(I)(\theta^S)^2 + (1-p)[1-\gamma(I)](\theta^R)^2\big]}. \tag{4.3}$$

This is a weighted average of the rates the bank would choose if it lent to each credit type separately. Screening changes those weights by altering which applicants are likely to be approved. In the benchmark calibration, more precise screening shifts weight toward safe borrowers and lowers the conditional optimal rate, whereas higher funding costs raise it.

The bank also decides how much to invest in screening. At a given rate, higher precision increases the mass of approved safe borrowers and reduces the mass of risky borrowers mistakenly approved. The optimal interior intensity equates these marginal benefits with the cost of screening,

$$C'(I) = \underbrace{\frac{1}{2}\left[pD_b^S m_b^S - (1-p)D_b^R m_b^R\right]}_{\Lambda(R_b)}. \tag{4.4}$$

The first component reflects additional profitable safe lending; the second reflects avoided losses on risky loans. At a fixed rate, the marginal benefit $\Lambda(R_b)$ does not depend on I, while marginal screening cost is increasing. Hence the conditional screening choice is unique. In equilibrium, however, pricing and screening are jointly determined, since the rate affects both application composition and the return to information acquisition. Equations (4.3)

and (4.4) characterize an interior candidate; the global policy comparison is addressed in the appendix.

4.2 Portfolio composition under monopoly

The risk composition of originated loans need not match that of the applicant pool. Borrowers first select into applications according to their willingness to borrow, and screening then makes safe applicants more likely than risky applicants to receive financing. More precise screening can therefore improve the composition of originated loans even when the posted rate, and hence the applicant pool, is unchanged. Since safe projects have a higher probability of success, the bank's expected default frequency is

$$\Omega_b^M = (1 - \theta^S) + (\theta^S - \theta^R)\frac{L_0^R}{L_0^S + L_0^R}. \tag{4.5}$$

Thus, portfolio risk depends on the share of risky *originated* loans rather than on the share of risky applicants.

Lemma 1 (Screening and bank portfolio composition)**.** *Suppose both credit types apply with positive probability and the bank lends following favorable signals. Holding the interest rate fixed, greater screening intensity strictly reduces the risky share of originated loans and the bank's expected default frequency. For $I > 0$, the risky share among originated loans is strictly below the risky share among bank applicants.*

The proof for this lemma is showed in Appendix A.3. We can see better the impact that screening has by looking at Figure 3. This illustrates how screening makes the bank's originated portfolio safer than its applicant pool. The lemma isolates the direct effect of screening at a given rate; when the rate also adjusts, changes in borrower participation can alter the resulting portfolio composition.

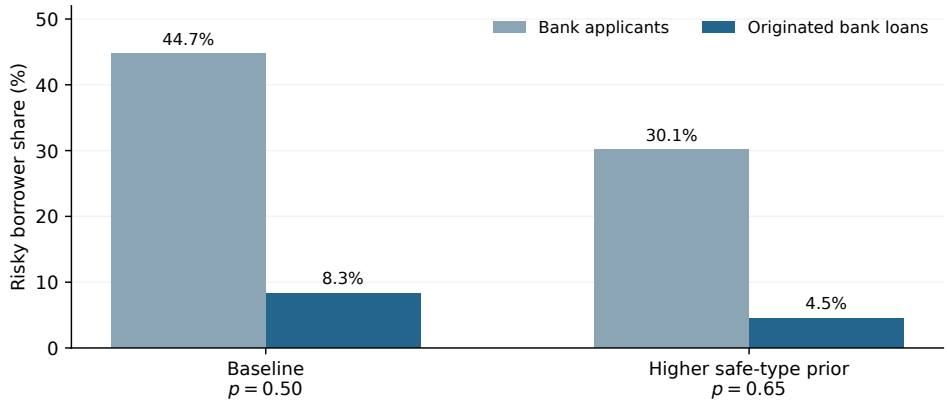


Figure 3: **Screening and loan composition.** Risky borrowers as a share of bank applicants and originated loans in the benchmark and in the higher-safe-prior calibration ($p = 0.50$ and $p = 0.65$, respectively; other parameters held fixed).

The monopoly benchmark therefore separates selection into applications from selection through screening. Platform entry introduces a further margin, as approved borrowers may instead accept a competing offer. The next section considers how this changes the bank's rate, screening decisions, and retained portfolio risk.

5 Competition with entrant digital platform

The bank-only benchmark establishes how borrower participation and screening determine credit allocation. Platform entry adds a further source of selection because now borrowers whom the bank would finance may instead borrow from a rival using information generated outside the credit market. We first identify which loans the platform displaces and then examine the bank's responses through pricing and screening. Distinguishing displacement at given lending decisions from the resulting equilibrium allocation is essential for understanding the effects on bank portfolio risk.

5.1 Credit allocation and equilibrium

Under a lending rule such that only those borrowers that produced a safe signal get credit, a truly safe bank applicant receives an offer with probability γ. However, he may still choose the platform when both lenders approve, provided he is a previous platform adopter. The mass of safe loans originated by the bank must also take into account the probability the borrower is a previous platform adopter. The probability that the platform can contest such a customer from the bank depends on the result of its screening signal. Therefore, the total mass of loans originated by the bank to true safe types is

$$L_b^S = p\gamma \left[(1 - \mu\delta) D_b^S + \mu\delta \widetilde{D}_b^S \right]. \tag{5.1}$$

Risky bank applicants get funded with probability $1 - \gamma$. That is, they only get funded by the bank if they are misclassified as safe types. Their originated mass is accordingly

$$L_b^R = (1 - p)(1 - \gamma) \left[(1 - \mu(1 - \delta)) D_b^R + \mu(1 - \delta) \widetilde{D}_b^R \right]. \tag{5.2}$$

For the platform, lending is restricted to previous adopters. Thus, every mass of loans needs to be weighted by the share μ. Safe originations depend on whether the bank also makes an acceptable offer, giving

$$L_p^S = \mu p\delta \left[(1 - \gamma) D_p^S + \gamma \widetilde{D}_p^S \right]. \tag{5.3}$$

Similarly as for the bank's case, true risky borrowers can be served by the platform. This depends on the probability the platform's signal misclassifies them. Hence, the corresponding loans by the platform going to risky borrowers can be expressed as

$$L_p^R = \mu(1 - p)(1 - \delta) \left[\gamma D_p^R + (1 - \gamma) \widetilde{D}_p^R \right]. \tag{5.4}$$

Note then, that each mass reflects the borrower's true type, the probabilities of receiving offers, and the ultimate choice of lender. Crucially, a favorable signal does not guarantee that a financed borrower is safe. This is at the heart of the adverse selection that lenders face.

Expected profits for each lender ℓ are the sum of originated loan masses weighted by type-specific margins, defined as $m_\ell^j \equiv \theta^j R_\ell - c_\ell$, less the bank's screening cost when applicable. General expressions for alternative approval policies are given in Appendix B. Our characterization of the results relies on fixing our attention to a particular equilibrium region, that we specify in the following part.

Equilibrium. The bank commits to $(R_b, I, \mathcal{M}_b)$, anticipating the platform's subsequent choice of rate and approval policy, including the option not to lend. In the interior benchmark region where both lenders approve favorable signals, let $R_p^*(R_b, I)$ denote the platform's optimal rate given the bank's commitment, suppressing adoption and other parameters. A competitive equilibrium consists of these sequentially optimal decisions and the induced borrower choices; a selection rule applies if the platform has multiple best responses. In the numerical benchmark, favorable-signal approval by both lenders is checked against alternative approval sets and nonentry. The associated calculations are discussed in Appendix B.

Benchmark competition region. At the benchmark rates, safe borrowers have overlapping acceptable offers, whereas risky borrowers do not. The interior pricing and screening conditions below apply to this region, where the platform's best-response rate increases with the bank's rate. Appendix B.6 considers participation boundaries and other pricing regions. The relative-displacement result that follows is not confined to this particular market-coverage configuration.

5.2 Which loans does the platform displace?

Consider the bank-monopoly loan masses L_0^S and L_0^R evaluated at the same bank rate and screening intensity as under entry. Define $\Delta_j \equiv D_b^j - \widetilde{D}_b^j$ as the reduction in type-j bank demand when a competing offer is available. Equations (5.1) and (5.2) imply that the platform displaces $\mu p \gamma \delta \Delta_S$ safe loans and $\mu(1-p)(1-\gamma)(1-\delta)\Delta_R$ risky loans. The effect on bank portfolio quality therefore depends on the *relative* displacement of the two types. We assume positive adoption and positive bank originations of both types, with favorable-signal approval by both lenders.

Proposition 1 (Relative displacement and portfolio risk)**.** *At unchanged bank decisions, platform entry increases the bank's expected default frequency precisely when it displaces a larger proportion of safe than risky loans:*

$$\delta \frac{\Delta_S}{D_b^S} > (1-\delta)\frac{\Delta_R}{D_b^R}.$$

The proposition isolates selection through competing offers. In the benchmark, risky borrowers have no overlap of acceptable offers, so $\Delta_R = 0$. The platform draws away profitable safe loans without directly displacing risky bank lending. But risky-market noncoverage is not necessary: when both types are contested, bank portfolio quality still deteriorates if safe loans are displaced at a higher proportional rate. Appendix B.10 provides the accounting underlying this result.

At unchanged lending terms, more precise platform information strengthens this selection mechanism. The platform becomes more likely to approve safe borrowers and less likely to approve risky ones, increasing the displacement of safe bank loans and reducing any direct displacement of risky loans. This is a partial-equilibrium effect; the bank's adjustment of pricing and screening can alter the final outcome. Appendix C extends the argument to nonuniform adoption across borrower preferences.

The mechanism has counterparts in the evidence on lending by BigTech companies. For

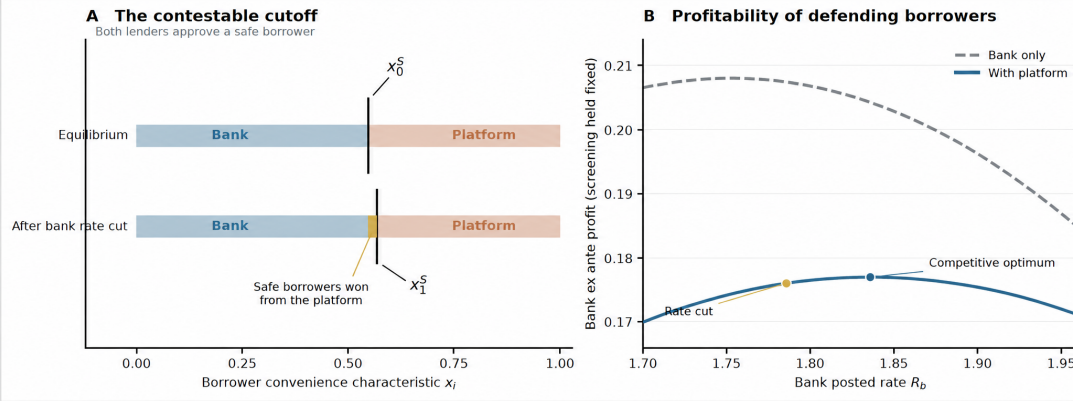


Figure 4: **Market stealing and the bank's common rate.** Panel A illustrates the safe borrowers gained through a bank-rate cut. Panel B shows bank profits at alternative rates with screening held fixed. Winning additional borrowers need not maximize overall profit.

instance, using Mercado Libre data from Argentina, Frost et al. (2019) show that transaction-based credit scores predict loan losses more accurately than conventional credit-bureau ratings. Chen et al. (2023) document reductions in lending and tighter loan-to-value ratios among traditional *non-bank* lenders facing greater BigTech penetration in China. Neither study directly measures the effect of entry on the default frequency of incumbent bank originations. Form the point of view of our model, Proposition 1 identifies the portfolio-composition prediction that is relevant for the testable implications for our mechanism.

5.3 Why does competition not necessarily lower the bank's rate?

A lower bank rate attracts safe borrowers near the lender-indifference cutoff $\bar{x}^S$. Figure 4 illustrates this market-stealing incentive. However, the bank cannot target a discount exclusively at those contested borrowers, since it must offer the lower rate to customers it would have retained anyway.

Within the benchmark competition region, the bank's profit equals its bank-only return less the expected margin on the safe loans diverted to the platform:

$$\Pi_b(R_b, I) = \Pi_b^M(R_b, I) - \mu p \gamma \delta \Delta_S m_b^S. \tag{5.5}$$

Taking account of the platform's best-response rate gives the bank's pricing condition,

$$\frac{\partial \Pi_b^M}{\partial R_b} = \mu p \gamma \delta \theta^S \left[\Delta_S - \frac{1+\rho_p}{2t} m_b^S \right], \tag{5.6}$$

where $\rho_p \equiv \partial R_p^*(R_b, I)/\partial R_b$ measures the platform's optimal rate response at a given bank screening intensity. The first term on the right captures the value of displaced safe lending, while the second reflects the change in displacement when both rates respond. On the left is the bank-only trade-off between higher repayments on retained loans and lower borrower participation.

Proposition 2 (Incumbent pricing)**.** *In the interior benchmark competition region, the bank's optimal rate at a given screening intensity exceeds its monopoly-case rate:* $R_b^C(I) > R_b^M(I)$.

The proposition explains why competing for the marginal borrower need not induce a lower *common* rate. A rate cut applies to the bank's entire retained loan book, not only to borrowers it might win from the platform. It can also attract risky applicants whose loans yield negative expected margins. Under the benchmark's participation conditions, these costs outweigh the gains from defending contested safe borrowers. A related result appears in Biancini and Verdier (2023), where platform entry can raise repayments for safer borrowers and change the quality of bank lending as investor participation on a two-sided platform affects borrower demand. Here, the higher common rate reflects the cost of repricing loans the bank would retain, while its riskier portfolio arises from the disproportionate displacement of safe borrowers by an information-rich entrant[1].

The bank's common-rate restriction also distinguishes our setting from Broecker (1990), where a small rate cut can transfer a positive mass of jointly approved borrowers, and Hauswald and Marquez (2006), where lenders can bid for individual borrowers. Here, a rate cut shifts the margin of borrower choice but also reprices loans the bank would retain

[1] Appendix B.11 establishes the conditional rate comparison.

anyway.

The higher-rate result is specific to the interior participation region. If safe bank demand is already saturated, a rate cut cannot create additional exclusive safe applications but can still attract borrowers with two offers. Defensive pricing can then become more attractive. Appendix B.6 provides an alternative equilibrium in which the competitive bank rate lies below its bank-only counterpart, illustrating how the price response changes across coverage regimes.

The evidence likewise cautions against identifying competitive effects from a simple ordering of loan rates. Liu et al. (2022) document smaller, shorter-lived BigTech business loans with higher annualized rates than conventional bank loans in China, including among borrowers with bank access. Such differences are consistent with the relevance of nonprice borrowing preferences, but do not identify how incumbent rates change following entry. Our pricing prediction concerns that response, conditional on borrower participation and the bank's common-rate constraint.

5.4 Why is screening less responsive than pricing?

Screening remains valuable for avoiding loss-making risky loans, even as platform entry reduces the return to identifying safe borrowers whom the bank may not retain. The bank's interior screening condition separates this displacement effect from the response of the platform's rate:

$$C'(I) = \Lambda(R_b) - \underbrace{\frac{\mu p \delta}{2} \Delta_S m_b^S}_{\text{displaced safe lending}} + \underbrace{\frac{\mu p \gamma \delta \theta^S}{2t} m_b^S \frac{\partial R_p^*(R_b, I)}{\partial I}}_{\text{platform repricing}}. \tag{5.7}$$

The bank-only marginal return $\Lambda(R_b)$ captures both additional safe lending and avoided losses on risky loans. Platform entry reduces the first benefit because some of the safe borrowers identified by the bank choose its competitor. The last term can offset this loss: in the benchmark, stronger bank screening induces a platform-rate adjustment that helps the bank retain profitable loans.

Screening therefore responds to offsetting forces. Its selection benefit persists, whereas the return to attracting safe customers is weakened by competition and partly restored through platform repricing. In the numerical benchmark, this produces a more modest adjustment in screening than in rates. The screening path is initially declining and then recovers slightly as the balance of these forces changes with adoption; the pattern is calibration-specific rather than a general prediction about the curvature of optimal screening. Figure 6 shows the equilibrium paths, and Appendix B.12 examines their components.

5.5 What does platform adoption change in equilibrium?

Platform adoption affects both the composition of applicants and the allocation of originated credit. These need not coincide, since borrowers can apply to both lenders while actual originations depend on imperfect approvals and the choice between competing offers. Figure 5 traces this distinction. Panel A presents the safe shares of the two applicant pools; Panel B compares safe and risky bank originations with the bank-only benchmark; and Panel C shows credit originated by each lender and in total. Across the benchmark, the bank loses a larger share of safe than risky loans, while the platform also finances borrowers who would otherwise remain without credit. The increase in total lending parallels De Fiore et al. (2023), where access to a digital marketplace acts as network collateral and relaxes firms' financing constraints. Here, additional credit arises through screening and borrower choice, even as the bank retains a riskier portfolio.

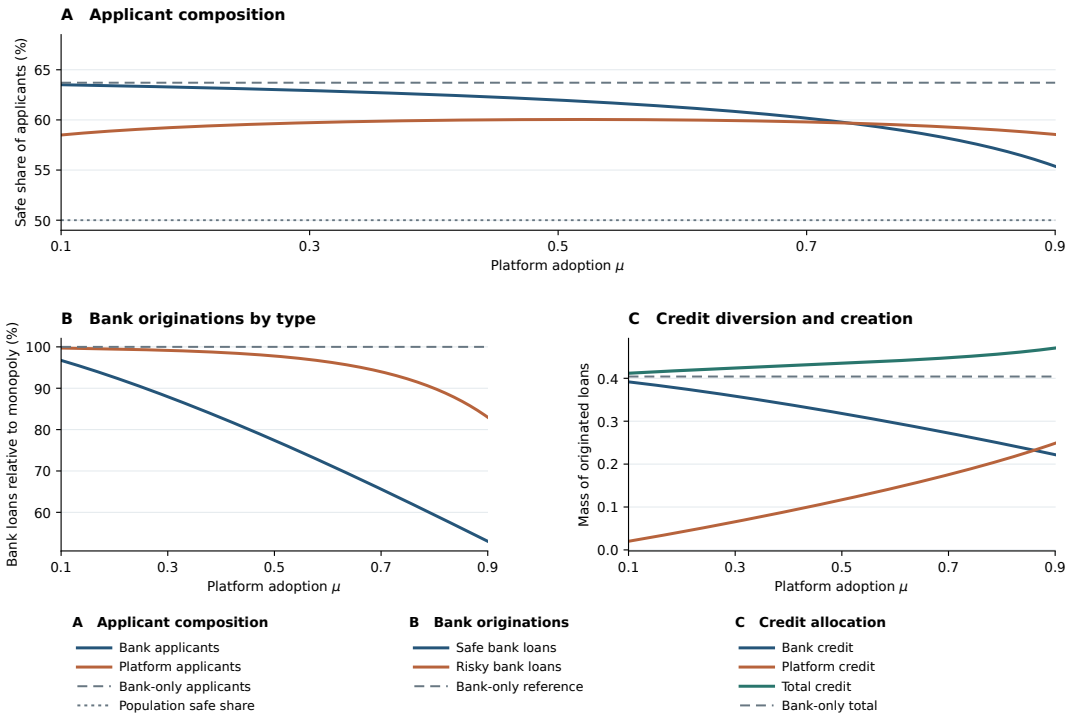


Figure 5: **From applications to originations.** Panel A compares the safe shares of bank and platform applicants; Panel B reports bank originations by true type relative to the optimized bank-only benchmark; Panel C shows loans by lender.

Figure 6 summarizes the bank's equilibrium response. Relative to monopoly, the bank charges a higher rate, adjusts screening comparatively little, and earns lower profits as the expected default frequency of its retained portfolio rises. The deterioration in loan quality reflects the reallocation of approved borrowers as well as the bank's endogenous decisions.

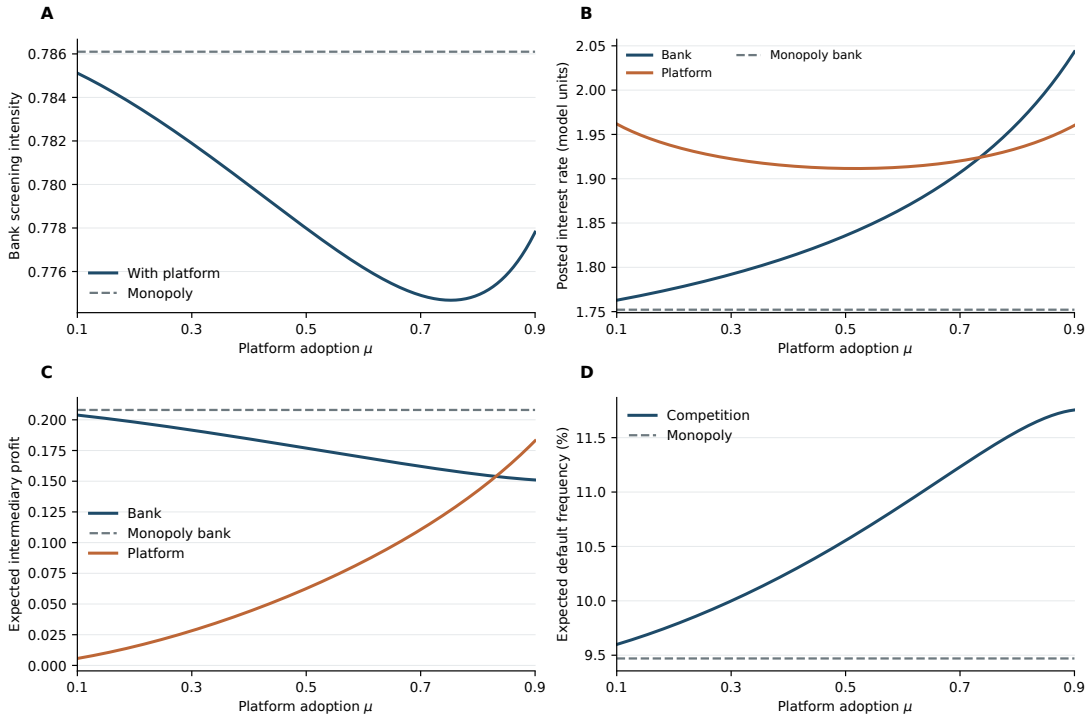


Figure 6: **Competition and the bank-only benchmark.** Screening intensity, posted rates, intermediary profits, and the bank's expected default frequency as platform adoption increases. Bank-only reference lines use the same benchmark calibration.

The distinction between applications and originations also yields an empirical implication. Where platform users overlap more with a bank's profitable customers, growing platform penetration should disproportionately displace safer bank loans, especially when platform data more accurately predict repayment risk. Identifying this mechanism requires observing the credit quality of applicants and originated borrowers, while accounting for changes in bank rates and screening. Appendix B.7 examines whether the incumbent would instead alter its decisions to deter entry; in the benchmark, accommodating the platform is more profitable than the examined deterrence strategies.

6 Comparative Statics

Platform entry changes the composition of credit retained by the bank. We now distinguish the role of the platform's information technology from that of funding costs. The first exercise holds the platform's reach fixed while changing its screening accuracy; the second changes the terms on which both intermediaries can finance loans.

6.1 How does better platform information affect the incumbent's portfolio?

A higher α raises the precision $\delta(\mu;\alpha)$ of the platform's signal at a given adoption level without expanding its potential customer base. In the benchmark region, better screening displaces additional safe bank loans but leaves risky bank originations unchanged at fixed lending decisions. Using (5.1) and (5.2), and noting that $\delta_\alpha \equiv \partial\delta/\partial\alpha > 0$ for $0 < \mu < 1$, we obtain

$$\left.\frac{\partial \Omega_b}{\partial \alpha}\right|_{R_b,R_p,I} = \frac{(\theta^S - \theta^R)\mu p \gamma \Delta_S L_b^R}{(L_b^S + L_b^R)^2}\,\delta_\alpha > 0. \tag{6.1}$$

This direct selection effect also extends to markets in which risky borrowers have overlapping acceptable offers: better platform screening then displaces fewer risky bank loans.

Proposition 3 (Platform information and bank portfolio selection)**.** *At unchanged lending decisions, greater platform signal precision raises the risky share of bank loans whenever both types are financed and a positive mass of loans is contested. It also weakly lowers the bank's ex ante profit and gross marginal return to screening.*

In the relevant region, safe-loan margins are positive and risky-loan margins are negative. More accurate platform screening reduces the bank's return to identifying profitable safe borrowers and, when risky offers overlap, leaves more risky lending opportunities with the incumbent. These are fixed-decision effects; equilibrium screening additionally reflects the platform's pricing response. Appendix D.1 proves the proposition for either market-coverage

configuration.

Figure 7 compares $\alpha \in \{1.25, 1.50, 1.75, 2\}$ at the original funding costs. Better platform information is associated with a higher bank rate and expected default frequency, lower bank profit, and a relatively small screening response. Screening remains valuable for avoiding loss-making risky loans, while platform repricing and a shrinking overlap of acceptable offers partly offset the direct loss of safe lending at high adoption. The screening paths therefore need not be monotonically ordered in α. We see then that platform adoption reinforces the selection mechanism through both reach and precision.

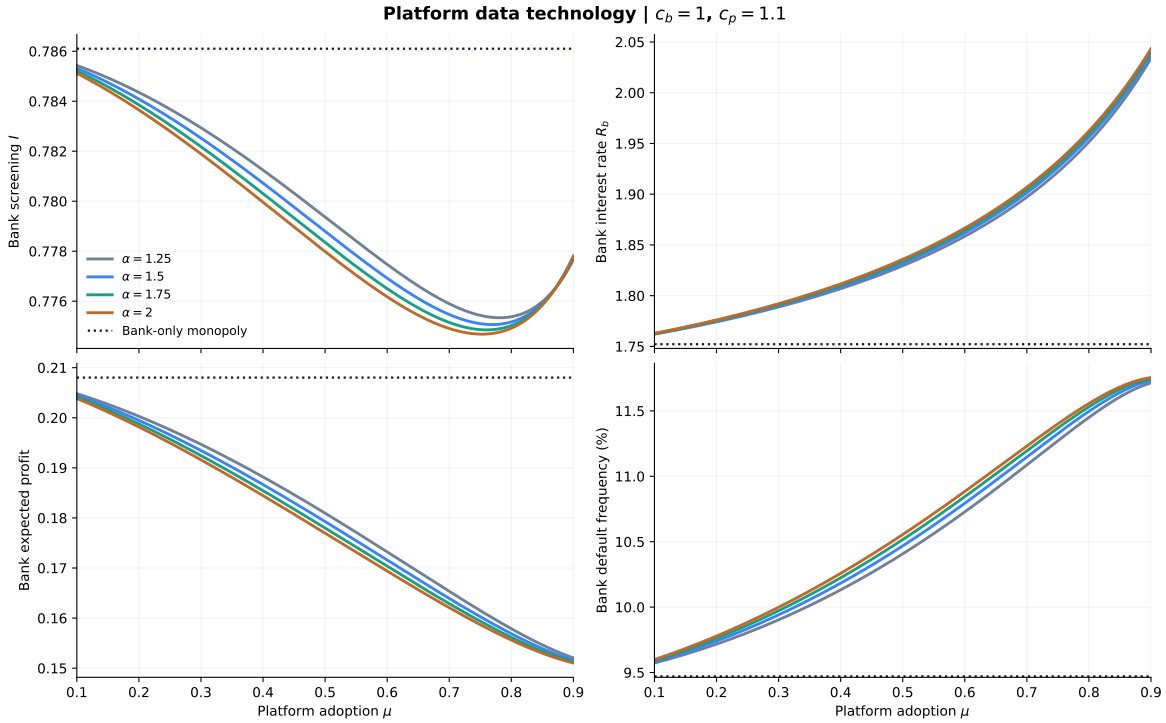


Figure 7: **Platform information and bank outcomes.** Screening intensity, posted bank rate, bank profit, and bank portfolio default frequency for $\alpha \in \{1.25, 1.50, 1.75, 2\}$, with $c_b = 1$ and $c_p = 1.1$. Horizontal reference lines represent the monopoly equilibrium.

6.2 When do funding costs change the extent of competition?

Funding costs change expected lending margins and, through rates, the overlap of acceptable offers. We compare the original $c_b = 1$ with $c_b = 1.1$, maintaining $c_p = \psi c_b$ and $\psi = 1.1$. Both lenders' funding costs therefore rise, and each competitive equilibrium is compared with its own same-cost monopoly benchmark.

Within the interior competition region, higher funding costs raise the bank's conditional optimal rate, but equilibrium pass-through need not be uniform. Higher repayments also shrink the overlap of acceptable offers for safe borrowers, which vanishes at $2Y^S - \theta^S(R_b + R_p) = t$. At this boundary, one-sided conditions replace the interior pricing condition, as discussed in Appendix D.2.

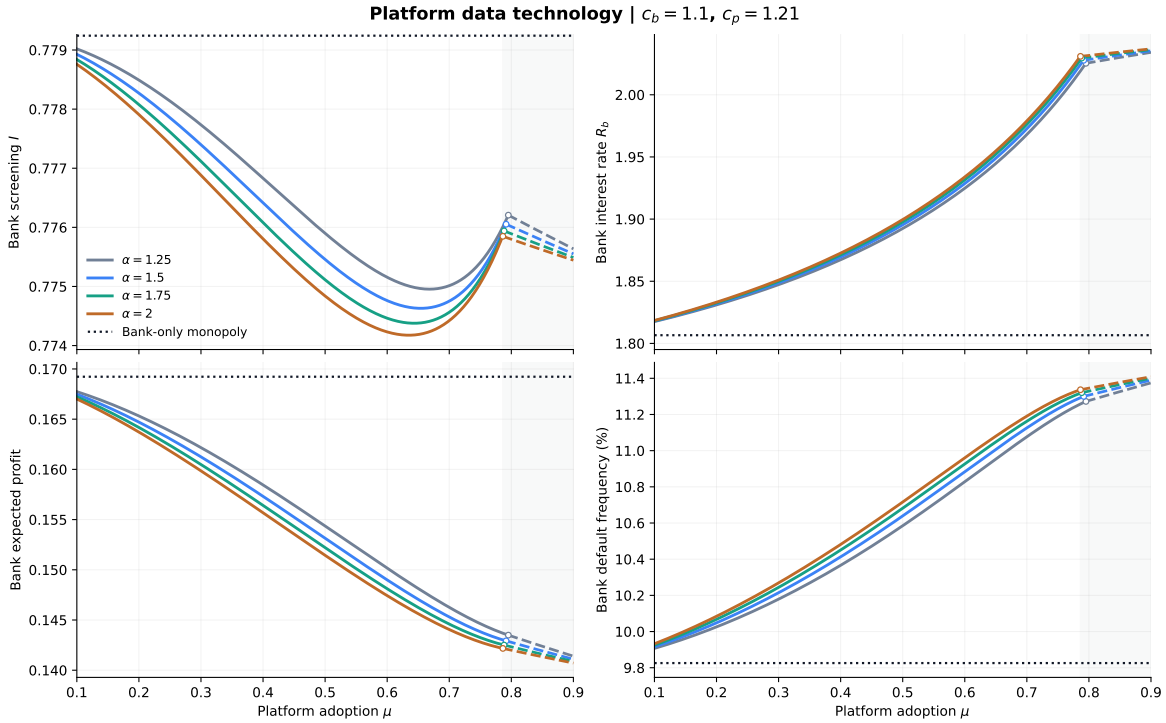


Figure 8: **Platform information under higher funding costs.** The same outcomes for $c_b = 1.1$, $c_p = 1.21$, with $\alpha \in \{1.25, 1.50, 1.75, 2\}$. Horizontal lines use the reoptimized monopoly at $c_b = 1.1$. Dashed portions indicate the binding safe-coverage frontier, not mixed strategies.

Figure 8 shows that the boundary is reached at high adoption, sooner when platform information is more precise. The ensuing changes in pricing and screening reflect a shift in which borrowers can be contested, not necessarily a discontinuous increase in bank portfolio risk. The interior pass-through result does not determine the equilibrium rate response across this boundary.

Taken together, the exercises distinguish information-driven selection from the participation effects of funding costs. More effective platform information increases the pressure on profitable bank lending opportunities, whereas tighter funding conditions change both margins and the extent of competition for those opportunities. These interactions help explain why the incumbent's rates, screening, and retained portfolio risk need not respond proportionately to platform expansion.

7 Efficient credit allocation and welfare

Platform entry may leave the bank with a riskier loan portfolio even while financing projects that would otherwise remain unfunded. We therefore examine productive efficiency, measured by expected project output net of funding and screening costs, and distinguish it from total welfare.

7.1 What prevents an efficient allocation of credit?

With $Y^S > c_p > c_b > Y^R$, a planner who observes true credit types funds all safe projects through the lower-cost bank, rejects risky projects, and has no need to screen. First-best productive surplus is consequently $W^{P,FB} = p(Y^S - c_b)$, independent of platform adoption.

In the decentralized economy, productive surplus is

$$W^P = \sum_{j \in \{S,R\}} \left[L_b^j (Y^j - c_b) + L_p^j (Y^j - c_p) \right] - C(I). \tag{7.1}$$

Because Y^j is expected output, default risk is already reflected in this expression. The resulting shortfall relative to the productive first-best is

$$W^{P,FB} - W^P = (Y^S - c_b)\big[p - L_b^S - L_p^S\big] + (c_p - c_b)L_p^S \\ + (c_b - Y^R)L_b^R + (c_p - Y^R)L_p^R + C(I). \tag{7.2}$$

The losses arise from safe projects left unfunded, the platform's higher funding cost on safe lending, mistaken risky loans, and screening expenditure. Each term is nonnegative under the maintained assumptions. The decomposition makes clear why expanding safe credit can improve efficiency despite diversion toward a more expensive intermediary.

7.2 Does platform entry improve credit allocation?

Platform entry brings two opposing effects. It can fund safe projects the bank would not originate, but can also shift lending to the higher-cost intermediary. Changes in the bank's own lending decisions further affect the outcome, so productive surplus need not rise monotonically with adoption.

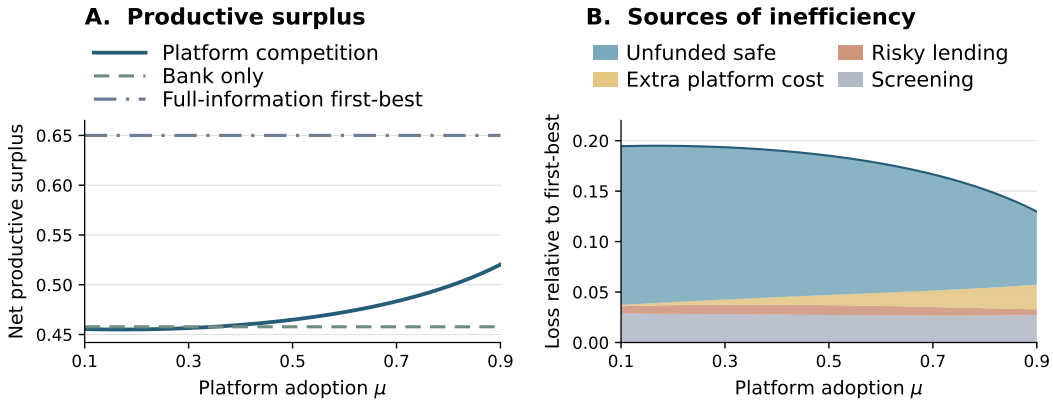


Figure 9: **Productive efficiency and its sources.** Panel A compares equilibrium net productive surplus with the bank-only equilibrium and the full-information first-best. Panel B decomposes the difference from the first-best into unfinanced safe projects, the platform's additional funding cost, mistaken financing of risky projects, and screening expenditure.

Figure 9 shows that unfunded safe projects account for most of the efficiency loss. As adoption expands, additional safe lending gradually outweighs the cost of credit diverted to the platform. Productive surplus initially falls slightly below the bank-only benchmark but subsequently exceeds it. Hence a deterioration in the bank's retained portfolio can coexist with a more efficient allocation of credit across the economy.[2]

8 Conclusion

Digital platforms can use information accumulated through non-financial activities to enter credit markets. This paper examines how such entry affects the lending decisions and portfolio risk of an incumbent bank. Platform adoption expands both the set of borrowers accessible to the entrant and the precision of its credit signal, while the bank invests in screening and offers a common interest rate.

Platform entry can increase the bank's expected default frequency through the disproportionate displacement of safe bank loans. This mechanism persists even when both borrower types may receive competing acceptable offers. The bank's response need not undo this selection effect. Cutting its common rate to defend contested borrowers would also lower repayments on loans it would otherwise retain, while screening remains valuable for avoiding loss-making risky projects. Better platform information strengthens the direct selection effect, and funding costs change which borrowers the lenders can contest.

A deterioration in the bank's retained portfolio does not necessarily imply a less efficient allocation of credit. The platform can finance safe projects that would otherwise go unfunded, allowing productive surplus to rise alongside the bank's heightened portfolio risk. Testing this mechanism requires evidence on both applicants and originated loans, and on how their composition changes with platform penetration, data quality, and incumbent lending decisions. Endogenizing ecosystem adoption and incorporating explicitly the intermediaries'

[2]For a comparison of the calculation when we net out the convenience costs for borrowers, please refer to Appendix E

balance sheets are natural future steps for assessing the implications of these portfolio changes for financial stability and macroprudential policy.

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A Bank monopoly: information, ex ante profits, and optimality

A.1 Applicant selection and posterior beliefs

The bank announces a common gross repayment R_b before observing individual applications or screening outcomes. For $j \in \{S, R\}$, let $D_b^j(R_b)$ be the fraction of type-j borrowers willing to apply for a bank loan. With the borrower utility specified in the main text, the exact application probability is

$$D_b^j(R_b) = \left[\frac{Y^j - \theta^j R_b}{t}\right]_0^1, \qquad [z]_0^1 \equiv \min\{1, \max\{0, z\}\}. \tag{A.1}$$

The associated mass of applicants and their safe-type prior are

$$\mathcal{A}_b = pD_b^S + (1-p)D_b^R, \qquad p_A = \Pr(S \mid A_b) = \frac{pD_b^S}{\mathcal{A}_b}, \tag{A.2}$$

where A_b denotes application to the bank and the conditional probability requires $\mathcal{A}_b > 0$. Thus, the composition of applications is potentially different from the population prior p, even before the bank receives any information.

For completeness, define $h_s = \Pr(m = s \mid A_b)$ and $h_r = \Pr(m = r \mid A_b)$. Under $\gamma = \gamma(I) = (1+I)/2$,

$$h_s = p_A\gamma + (1-p_A)(1-\gamma), \qquad h_r = p_A(1-\gamma) + (1-p_A)\gamma. \tag{A.3}$$

The probabilities that an applicant is truly safe after a favorable signal and truly risky after an unfavorable signal are, respectively,

$$\beta^S = \Pr(S \mid A_b, m = s) = \frac{p_A\gamma}{h_s}, \qquad \beta^R = \Pr(R \mid A_b, m = r) = \frac{(1-p_A)\gamma}{h_r}. \tag{A.4}$$

At $I = 0$ these become $\beta^S = p_A$ and $\beta^R = 1 - p_A$. These beliefs describe the information contained in the screening outcomes; *they are not additional weights in ex ante profit.* The latter is computed below directly from the unconditional joint masses of applications, approvals, and ultimately originated loans.

A.2 Loan origination and expected profits

Write $p_S = p$ and $p_R = 1 - p$, and define the expected margin on a loan to a *true* type-j borrower as

$$m_b^j(R_b) \equiv \theta^j R_b - c_b.$$

A type-j borrower applies with probability D_b^j and, conditional on applying, is approved after a favorable signal with probability $\Pr(m = s \mid j)$. Under the approval policy $M_b = \{s\}$, these probabilities are γ for safe borrowers and $1 - \gamma$ for risky borrowers. Hence the ex ante originated masses are exactly those of equation (4.1):

$$L_0^S = \underbrace{p}_{\text{safe share}} \underbrace{D_b^S}_{\text{application}} \underbrace{\gamma}_{\text{approval}}, \qquad L_0^R = \underbrace{(1-p)}_{\text{risky share}} \underbrace{D_b^R}_{\text{application}} \underbrace{(1-\gamma)}_{\text{approval}}. \tag{A.5}$$

Expected profit is therefore equation (4.2):

$$\Pi_b^M(R_b, I; \{s\}) = L_0^S m_b^S + L_0^R m_b^R - C(I), \qquad C(I) = \frac{\kappa I^2}{1 - I}. \tag{A.6}$$

No loan-specific funding cost is incurred by rejected applicants, and the information-acquisition cost is paid once, not per application or loan. In particular, equation (A.6) does not multiply L_0^S or L_0^R by the posterior probabilities in (A.4). The unconditional originated-loan masses in (A.5) are the sole weights in the profit expression; posterior beliefs describe signal informativeness.

A.3 Proof of Lemma 1

With positive demand of both types, the risky-to-safe odds among applicants equal $(1-p)D_b^R/(pD_b^S)$. Under favorable-signal approval the corresponding odds among originated loans multiply this expression by $(1-\gamma)/\gamma = (1-I)/(1+I)$. For $0 < I < 1$, the latter factor is strictly below one, establishing the first comparison. Holding the rate fixed,

$$\frac{\partial}{\partial I} \log \frac{L_0^R}{L_0^S} = -\frac{2}{1-I^2} < 0.$$

Since $\theta^S > \theta^R$, equation (4.5) then implies that the risky share and expected default frequency decrease strictly with screening. This partial effect does not sign the outcome when the posted rate or approval policy is reoptimized.

A.4 Alternative approval policies

Let $e_s, e_r \in \{0,1\}$ indicate whether the bank approves a borrower after signals s and r, respectively. The conditional offer probabilities are

$$q_b^S = e_s\gamma + e_r(1-\gamma), \qquad q_b^R = e_s(1-\gamma) + e_r\gamma. \tag{A.7}$$

For any R_b and I, the ex ante objective for the corresponding policy is

$$\Pi_b^M(R_b, I; e_s, e_r) = pD_b^S q_b^S m_b^S + (1-p)D_b^R q_b^R m_b^R - C(I). \tag{A.8}$$

This formula covers favorable-only lending $(e_s, e_r) = (1,0)$, unfavorable-only lending $(0,1)$, pooling $(1,1)$, and no lending $(0,0)$. Under pooling, information does not affect approval probabilities and $I = 0$ is optimal; under no lending, $I = 0$ and profits are zero.

Assumption 2 implies that any risky applicant willing to accept the bank contract has $m_b^R < 0$. When $m_b^S \geq 0$, the profit difference at a common (R_b, I) between approving only

favorable signals and approving only unfavorable signals is

$$\Pi_b^M(R_b, I; 1, 0) - \Pi_b^M(R_b, I; 0, 1) = (2\gamma - 1)\left[pD_b^S m_b^S - (1-p)D_b^R m_b^R\right] \geq 0. \tag{A.9}$$

When $m_b^S < 0$, both true-type margins are nonpositive for borrowers who accept credit and no lending weakly dominates unfavorable-only lending. Thus, under the maintained primitives, unfavorable-only lending cannot strictly dominate both favorable-only lending and no lending. Nevertheless, the monopoly optimum is obtained only after optimizing and comparing the payoffs of the remaining policies over all admissible prices and screening intensities, including participation boundaries.

A.5 Conditional optimality and global solution

For favorable-signal lending write

$$a_S(I) \equiv p\gamma(I), \qquad a_R(I) \equiv (1-p)[1-\gamma(I)].$$

Then $\Pi_b^M = \sum_j a_j(I) D_b^j m_b^j - C(I)$. In any region where $0 < D_b^S, D_b^R < 1$, differentiation at fixed I gives the interest-rate condition stated in equation (4.3):

$$0 = \frac{\partial \Pi_b^M}{\partial R_b} = \sum_{j \in \{S,R\}} a_j(I) \left[\theta^j D_b^j - \frac{\theta^j}{t} m_b^j\right] \tag{A.10}$$

$$= \frac{1}{t} \sum_{j \in \{S,R\}} a_j(I) \theta^j \left(Y^j + c_b - 2\theta^j R_b\right). \tag{A.11}$$

Here the first term in square brackets is the marginal revenue effect on existing loans and the second captures the endogenous reduction in applications. The conditional optimal price within this interior cell is

$$R_b^M(I) = \frac{a_S(I)\theta^S(Y^S + c_b) + a_R(I)\theta^R(Y^R + c_b)}{2\left[a_S(I)(\theta^S)^2 + a_R(I)(\theta^R)^2\right]}. \tag{A.12}$$

At a fixed R_b, since $\gamma'(I) = 1/2$, the screening condition in equation (4.4) is

$$\frac{\partial \Pi_b^M}{\partial I} = 0 \quad \Longleftrightarrow \quad \underbrace{\frac{1}{2}\left[pD_b^S m_b^S - (1-p)D_b^R m_b^R\right]}_{\Lambda(R_b)} = \underbrace{\kappa\left[\frac{1}{(1-I)^2} - 1\right]}_{C'(I)}. \tag{A.13}$$

The screening benefit $\Lambda(R_b)$ includes the gains from identifying safe borrowers and avoiding negative-margin risky borrowers. $C''(I) = 2\kappa/(1-I)^3 > 0$, so for each fixed rate the unique favorable-policy screening choice is

$$I^M(R_b) = \begin{cases} 1 - \sqrt{\dfrac{\kappa}{\kappa + \Lambda(R_b)}}, & \Lambda(R_b) > 0, \\ 0, & \Lambda(R_b) \leq 0. \end{cases} \tag{A.14}$$

An equivalent one-dimensional characterization profiles screening out:

$$\max_{I \in [0,1)} \Pi_b^M(R_b, I; \{s\}) = \frac{K_S(R_b) + K_R(R_b)}{2} + \left[\sqrt{\kappa + \max\{\Lambda(R_b), 0\}} - \sqrt{\kappa}\right]^2, \tag{A.15}$$

where $K_S = pD_b^S m_b^S$ and $K_R = (1-p)D_b^R m_b^R$. This expression continues to hold when either demand is zero or one. The full monopoly optimum compares its global maximum over R_b with pooling and nonlending. The conditions (A.10) and (A.13) apply only at a smooth interior optimum.

At participation boundaries, which occur at $R_b = (Y^j - t)/\theta^j$ and $R_b = Y^j/\theta^j$, D_b^j remains continuous but has a kink. On a differentiable segment its rate derivative is $-(\theta^j/t)$ if $0 < D_b^j < 1$ and zero when demand is locally constant. The exact profit derivative is then

$$\frac{\partial \Pi_b^M}{\partial R_b} = \sum_j a_j \left[\theta^j D_b^j + m_b^j \frac{\partial D_b^j}{\partial R_b}\right].$$

At a candidate interior kink R_0, the necessary one-sided condition is $\Pi'_{b,-}(R_0) \geq 0 \geq \Pi'_{b,+}(R_0)$, with one-sided derivatives of the optimized, screened payoff when screening is profiled out. A global maximum must still be compared across the smooth cells and ap-

proval policies.

A.6 Rate, screening, and portfolio-risk implications

Within the interior favorable-policy cell, the conditional rate responds positively to bank funding cost:

$$\left.\frac{\partial R_b^M(I)}{\partial c_b}\right|_I = \frac{a_S(I)\theta^S + a_R(I)\theta^R}{2\left[a_S(I)(\theta^S)^2 + a_R(I)(\theta^R)^2\right]} > 0. \tag{A.16}$$

For the conditional response to screening, define $w_j = a_j(I)(\theta^j)^2$ and $r_j = (Y^j + c_b)/(2\theta^j)$. Direct differentiation of (A.12) yields

$$\frac{dR_b^M(I)}{dI} = \frac{p(1-p)(\theta^S)^2(\theta^R)^2}{2(w_S + w_R)^2}(r_S - r_R). \tag{A.17}$$

This derivative is negative when $r_S < r_R$, as in the benchmark; it is not necessarily negative for all primitives.

For favorable-signal bank lending, the expected default frequency is

$$\Omega_b^M = \frac{L_0^S(1-\theta^S) + L_0^R(1-\theta^R)}{L_0^S + L_0^R} = (1-\theta^S) + (\theta^S - \theta^R)\frac{L_0^R}{L_0^S + L_0^R}. \tag{A.18}$$

Moreover, conditional on positive loan masses,

$$\frac{L_0^R}{L_0^S} = \frac{1-p}{p}\frac{1-I}{1+I}\frac{D_b^R}{D_b^S}.$$

Thus portfolio composition depends separately on population odds, screening accuracy, and borrower selection into applications. With interior demand and $R_b = R_b^M(I)$,

$$\frac{d}{dI}\log\frac{L_0^R}{L_0^S} = -\frac{2}{1-I^2} + \left[\frac{\theta^S}{Y^S - \theta^S R_b} - \frac{\theta^R}{Y^R - \theta^R R_b}\right]\frac{dR_b^M(I)}{dI}. \tag{A.19}$$

If $\theta^S Y^R \geq \theta^R Y^S$ and $dR_b^M/dI \leq 0$, this derivative is negative. The qualification matters: for arbitrary primitives, the endogenous rate response need not reinforce the direct screening

effect.

Finally, at a strict smooth interior optimum the screening-cost comparative static follows from the implicit condition $\Lambda(R_b^M(I)) = C'(I)$. With $F(I,\kappa) = \Lambda(R_b^M(I)) - \kappa[(1-I)^{-2}-1]$ and $F_I < 0$,

$$\frac{dI^M}{d\kappa} = \frac{(1-I^M)^{-2}-1}{F_I} < 0.$$

The implied rate and risk responses inherit the stated conditional sign restrictions. None of these derivatives establishes global monotonicity across changes in participation or approval policies.

B Platform competition: ex ante loan masses and profit accounting

B.1 Joint events and conditional demands

Retain $p_S = p$, $p_R = 1-p$ and the conditional participation probabilities D_b^j, D_p^j defined in Section 3. Because lenders cannot condition their rates on private convenience characteristics, an eligible type-j borrower can apply to both lenders. Let $\widetilde{D}_\ell^j$ denote the share choosing lender ℓ when both lenders extend an acceptable offer. For an arbitrary pair of posted rates these quantities are computed from

$$\bar{x}^j = \frac{1}{2} + \frac{\theta^j(R_p - R_b)}{2t}, \qquad \widetilde{D}_b^j = \min\{D_b^j, [\bar{x}^j]_0^1\}, \qquad \widetilde{D}_p^j = \min\{D_p^j, [1-\bar{x}^j]_0^1\}.$$

These formulas incorporate the outside option and permit a gap in acceptable offers. They reduce to $\bar{x}^j$ and $1-\bar{x}^j$ only in an interior covered market. In particular, when the acceptable offer sets are disjoint, $\widetilde{D}_b^j = D_b^j$ and $\widetilde{D}_p^j = D_p^j$.

Let q_b^j be the probability of a bank offer conditional on a potential type-j application and

let q_p^j be the corresponding platform probability. Under arbitrary signal-approval policies,

$$q_b^S = e_{b,s}\gamma + e_{b,r}(1-\gamma), \quad q_b^R = e_{b,s}(1-\gamma) + e_{b,r}\gamma,$$

$$q_p^S = e_{p,s}\delta + e_{p,r}(1-\delta), \quad q_p^R = e_{p,s}(1-\delta) + e_{p,r}\delta,$$

where $e_{\ell,k} \in \{0,1\}$. The platform can lend only to adopters, of mass μ, while the bank can lend to all borrowers. Both signals are independent conditional on the true type, and adoption is independent of true type and convenience.

B.2 Originations and expected profits

Partition type-j bank lending by whether a competing platform offer is made. Ex ante origination masses are

$$L_b^j = \underbrace{p_j q_b^j (1-\mu q_p^j) D_b^j}_{\text{no platform offer}} + \underbrace{p_j \mu q_b^j q_p^j \widetilde{D}_b^j}_{\text{both offers; bank chosen}}, \tag{B.1}$$

$$L_p^j = \underbrace{\mu p_j q_p^j (1-q_b^j) D_p^j}_{\text{no bank offer}} + \underbrace{\mu p_j q_p^j q_b^j \widetilde{D}_p^j}_{\text{both offers; platform chosen}}. \tag{B.2}$$

The two terms for a given intermediary are mutually exclusive; loans are neither omitted nor counted twice. Integrating over the unobserved convenience characteristic is already contained in the D and $\widetilde{D}$ terms.

Since L_ℓ^j is the *unconditional originated mass of true type* j, expected profits are simply

$$\Pi_b = \sum_{j\in\{S,R\}} L_b^j(\theta^j R_b - c_b) - C(I), \qquad \Pi_p = \sum_{j\in\{S,R\}} L_p^j(\theta^j R_p - c_p). \tag{B.3}$$

No applicant posterior enters this expression as a separate weight. Posterior beliefs govern the informational interpretation of the signal; the joint offer and choice probabilities determine the numbers of loans actually originated.

Under the favorable-only policies $M_b = M_p = \{s\}$, one has $(q_b^S, q_b^R) = (\gamma, 1-\gamma)$ and $(q_p^S, q_p^R) = (\delta, 1-\delta)$. Substituting these probabilities into (B.1) and (B.2) yields the bank masses in (5.1) and (5.2), and the platform masses in (5.3) and (5.4). In the benchmark safe-covered/risky-uncovered region, $\widetilde{D}_b^R = D_b^R$ and $\widetilde{D}_p^R = D_p^R$, whence

$$L_b^S = p\gamma\big[D_b^S - \mu\delta(D_b^S - \widetilde{D}_b^S)\big], \qquad L_b^R = (1-p)(1-\gamma)D_b^R, \tag{B.4}$$

$$L_p^S = \mu p\delta\big[(1-\gamma)D_p^S + \gamma\widetilde{D}_p^S\big], \qquad L_p^R = \mu(1-p)(1-\delta)D_p^R.$$

Defining $\Delta_S \equiv D_b^S - \widetilde{D}_b^S$ and using the monopoly profit function evaluated at the *same* bank rate and screening investment yields the exact identity

$$\Pi_b(R_b, I; R_p) = \Pi_b^M(R_b, I) - \mu p\gamma(I)\delta\Delta_S\,(\theta^S R_b - c_b), \tag{B.5}$$

which reproduces equation (5.5) after substituting the platform's best-response rate $R_p^*(R_b, I)$. This is not a comparison of reoptimized monopoly and competitive profits.

B.3 Conditional signal probabilities and lender choice

For clarity, the probability that a bank applicant is safe conditional on receiving a favorable bank signal remains β^S from Appendix A.1: application to the bank depends on its posted rate, not on the realization of the unobserved platform signal. The platform's applicant prior is

$$p_{A,p} = \frac{pD_p^S}{pD_p^S + (1-p)D_p^R},$$

when its applicant mass is positive. Its corresponding favorable-signal safe posterior is

$$\beta_p^S = \frac{p_{A,p}\delta}{p_{A,p}\delta + (1-p_{A,p})(1-\delta)}.$$

These posterior probabilities generally differ from the true-type composition of originated loans, because the latter also reflects competition after both signals have been realized:

$$\Pr(S \mid \text{bank loan}) = \frac{L_b^S}{L_b^S + L_b^R}, \qquad \Pr(S \mid \text{platform loan}) = \frac{L_p^S}{L_p^S + L_p^R}.$$

The distinction between applicants, approved borrowers and originated loans is therefore essential for both profits and bank portfolio risk. Global price optimization must use the piecewise conditional demands above; the interior optimality conditions in Section 5 do not apply at participation boundaries.

B.4 Platform pricing and best responses

The ex ante bank and platform loan masses are defined in (B.1) and (B.2), with profits given by (B.3). These expressions apply to every approval policy and pricing region.

The platform's exact value after observing the bank commitment is

$$V_p(R_b, I, M_b; \mu) = \max\left\{0, \sup_{R_p,\, M_p \neq \varnothing} \Pi_p(R_p, M_p; R_b, I, M_b)\right\}.$$

The first alternative is no lending. The platform's global best response must compare all admissible offer policies $M_p \in \{\{s\}, \{r\}, \{s, r\}\}$ and all applicable pricing cells.

In the safe-covered/risky-uncovered region with $M_b = M_p = \{s\}$, write $\gamma = \gamma(I)$ and $\delta = \delta(\mu)$. The relevant platform volumes simplify to

$$\frac{L_p^S}{\mu p \delta} = (1-\gamma) D_p^S + \gamma(1 - \bar{x}^S), \qquad \frac{L_p^R}{\mu(1-p)(1-\delta)} = D_p^R.$$

Set $w_S = p\delta$, $w_R = (1-p)(1-\delta)$, and define

$$u_S = (1-\gamma)\frac{Y^S}{t} + \frac{\gamma}{2} + \frac{\gamma \theta^S R_b}{2t}, \quad v_S = \frac{\theta^S}{t}\left(1 - \frac{\gamma}{2}\right),$$
$$u_R = \frac{Y^R}{t}, \qquad\qquad\qquad\quad v_R = \frac{\theta^R}{t}.$$

Then $L_p^j = \mu w_j(u_j - v_j R_p)$ and $\Pi_p = \mu \sum_j w_j(\theta^j R_p - c_p)(u_j - v_j R_p)$. Differentiating gives

$$0 = \frac{1}{\mu}\frac{\partial \Pi_p}{\partial R_p} = \sum_{j \in \{S,R\}} w_j \left[\theta^j u_j + c_p v_j - 2\theta^j v_j R_p\right]. \tag{B.6}$$

Its second derivative is $-2\mu \sum_j w_j \theta^j v_j < 0$ for $\mu > 0$. The conditional interior best response is therefore

$$R_p^*(R_b, I; \mu) = \frac{\sum_j w_j(\theta^j u_j + c_p v_j)}{2\sum_j w_j \theta^j v_j}, \qquad \rho_p \equiv \frac{\partial R_p^*}{\partial R_b} = \frac{w_S \gamma (\theta^S)^2}{4t \sum_j w_j \theta^j v_j} > 0.$$

Here μ affects the conditional price through $\delta(\mu)$ and the bank's response, rather than its multiplicative effect on platform size. Throughout the smooth benchmark cell, R_p^* denotes this unique conditional best-response rate; outside it, the platform's globally optimal rate can be set-valued and need not be differentiable. The conditional optimum is valid only if the resulting prices satisfy the assumed coverage inequalities and outperform alternative platform approval policies and pricing cells. In particular, the platform's rate cannot be inferred from (B.6) when its best response is at a kink or is nonentry.

B.5 Competition: the bank's problem, first-order conditions, and equilibrium

With favorable-signal offers, define $a_S = p\gamma$, $a_R = (1-p)(1-\gamma)$ and $\Delta_S \equiv D_b^S - \widetilde{D}_b^S$. In the benchmark region $L_b^R = a_R D_b^R$, whereas $L_b^S = a_S(D_b^S - \mu\delta\Delta_S)$. The bank's ex ante return, evaluated along the platform's response, is exactly

$$\Pi_b^C(R_b, I) = \Pi_b^M(R_b, I) - \mu a_S \delta \Delta_S m_b^S. \tag{B.7}$$

No assumption about the platform's signal being superior to the bank's is needed for this identity. It expresses the profit from the bank's lost *safe* originations at the same bank

choices; it does not compare the two optimized equilibria.

Let $F_M = \partial \Pi_b^M / \partial R_b$ hold screening fixed. Within the smooth benchmark cell, $\Delta_S = (Y^S - t/2 - \theta^S(R_b + R_p)/2)/t$ and, along the platform's price response,

$$\frac{d\Delta_S}{dR_b} = -\frac{\theta^S}{2t}(1 + \rho_p).$$

Thus the bank's conditional price first-order condition is

$$F_M(R_b, I) = \mu a_S \delta \theta^S \left[\Delta_S - \frac{1 + \rho_p}{2t} m_b^S \right]. \tag{B.8}$$

The two terms on the right have distinct economic meanings. The first captures the infra-marginal profitable safe business lost to the platform; the second captures how changing the bank rate and inducing platform repricing alter the amount of that displacement. The presence of direct market stealing therefore does not, by itself, imply a lower optimal common bank rate.

Similarly, $\gamma'(I) = 1/2$ and $d\Delta_S/dI = -(\theta^S/2t)\partial R_p^*/\partial I$. Differentiating (B.7) gives

$$C'(I) = \Lambda(R_b) - \frac{\mu p \delta}{2} \Delta_S m_b^S + \frac{\mu p \gamma \delta \theta^S}{2t} m_b^S \frac{\partial R_p^*}{\partial I}. \tag{B.9}$$

The last term is a strategic response term; it would be absent if the platform set its rate before the bank chose screening. For completeness, if $N(I) = \sum_j w_j(\theta^j u_j + c_p v_j)$ and $H(I) = \sum_j w_j \theta^j v_j$, the response is $\partial_I R_p^* = (N_I - 2R_p^* H_I)/(2H)$, which need not have a uniform sign away from the benchmark.

For each bank choice (R_b, I, M_b), let $\mathrm{BR}_p(R_b, I, M_b)$ be the argmax correspondence of the platform's objective in (B.3), including nonentry. A pure-strategy Stackelberg equilibrium consists of a bank commitment (R_b^*, I^*, M_b^*) and a specified platform best-response selection $\sigma_p \in \mathrm{BR}_p$ such that (R_b^*, I^*, M_b^*) maximizes the bank's induced ex ante profit, with applications, signals and contract choices implemented as specified in the model. If the follower has

multiple exact maximizers, a selection or tie-breaking convention is necessary to make the leader's problem single-valued; the numerical benchmark does not rely on an observed strict follower tie along its interior equilibrium path. Equations (B.6)–(B.9) characterize an *interior candidate* for given approval policies. They are not a substitute for global comparison with boundaries, other approval sets and nonentry.

B.6 Non-interior rates, coverage changes, and one-sided optimality

For any real z, let $[z]_0^1 \equiv \max\{0, \min\{1, z\}\}$. Using the participation and preference thresholds defined in the main text, the correct demands at arbitrary posted rates are

$$D_b^j = [\bar{x}_b^j]_0^1, \quad D_p^j = [1 - \bar{x}_p^j]_0^1, \quad \widetilde{D}_b^j = [\min\{\bar{x}_b^j, \bar{x}^j\}]_0^1, \quad \widetilde{D}_p^j = [1 - \max\{\bar{x}_p^j, \bar{x}^j\}]_0^1. \tag{B.10}$$

The region in which competing offers are both acceptable is determined by $2Y^j - \theta^j(R_b + R_p) \geq t$; the strict reverse inequality gives an uncovered interval. Other boundaries arise when a lender's participation threshold reaches 0 or 1, or when $\bar{x}^j$ reaches the endpoint of the borrower-characteristic interval. Hence a lender's optimal interest rate may lie at a participation kink, at the transition between covered and uncovered demand, or at an admissible endpoint.

For example, when no truncation at 0 or 1 is active, the derivatives of demand for a borrower receiving both offers depend on the constraint that limits the lender's allocation:

binding condition	$\partial \widetilde{D}_b^j / \partial R_b$	$\partial \widetilde{D}_b^j / \partial R_p$
$\bar{x}_b^j < \bar{x}^j$ (bank participation)	$-\theta^j / t$	0
$\bar{x}^j < \bar{x}_b^j$ (relative preference)	$-\theta^j / (2t)$	$\theta^j / (2t)$

binding condition	$\partial \widetilde{D}_p^j/\partial R_b$	$\partial \widetilde{D}_p^j/\partial R_p$
$\bar{x}_p^j > \bar{x}^j$ (platform participation)	0	$-\theta^j/t$
$\bar{x}^j > \bar{x}_p^j$ (relative preference)	$\theta^j/(2t)$	$-\theta^j/(2t)$

All derivatives vanish when the relevant allocation is locally clamped at zero or one. Consequently, the standard price-competition margin applies only when relative preference binds, whereas the margin of new credit participation applies when the lender's own acceptance threshold binds. At equality of the thresholds there is no single classical derivative, and the pertinent one-sided conditions must be used.

On each smooth region, conditional demands are affine functions of the posted rates, so platform profit at a fixed bank commitment and approval policy is quadratic in R_p. The exact follower optimization can therefore compare (i) stationary points inside each smooth pricing cell, (ii) cell endpoints, and (iii) all signal-offer policies. The incumbent then compares its induced payoff across the follower's pricing regions and its own approval policies. At a kink, the correct local condition is a nonnegative left derivative and nonpositive right derivative (with modifications at domain endpoints), not the interior first-order equality. A crossing between follower best responses can also make the leader's induced payoff nonsmooth; the bank's global comparison must retain those candidate points.

One implication is that the higher-rate result in the benchmark interior cell does not rule out lower bank rates in other cells. For a concrete admissible example, retain the benchmark $p = 0.5$, $(\theta^S, \theta^R) = (0.95, 0.25)$, $Y^R = 0.80$, $c_b = 1$, $\kappa = 0.01$, and $\alpha = 2$, and set $Y^S = 2.25$, $t = 0.50$, and $c_p = 1.16$. Both lenders continue to face negative-NPV truly risky projects, $Y^R < c_b < c_p$. At the competitive solution, both credit types have overlapping acceptable contracts when both offers arrive; thus the original risky-uncovered formula does not carry over. In the associated *bank-only* monopoly, the optimal rate is the safe full-participation boundary $(Y^S - t)/\theta^S = 1.8421$, where its smooth interior pricing equation is inapplicable. At $\mu = 0.90$, the competitive optimum has $R_b = 1.8186 < R_b^M$, $I = 0.7814$, and favorable-signal offers by both lenders. The competitive bank default frequency is approximately

13.86%, compared with 9.56% under the same-parameter monopoly. Thus the interest-rate sign can reverse without altering the assumption $Y^R < c_\ell$ or the central portfolio-selection mechanism.

The transition can be assessed using the one-sided marginal-profit conditions at the safe participation boundary; the corresponding illustrative figure is retained in the earlier numerical audit but is not required for the analytical result.

B.7 Entry blockade, deterrence, and accommodation

There are three distinct notions. Entry is *blockaded* at a bank-only monopoly commitment if the entrant's maximal operating profit is nonpositive without any defensive change by the incumbent. Entry is *deterred* if the bank deliberately chooses an alternative (R_b, I, M_b) making the entrant's maximal operating profit nonpositive. Entry is *accommodated* when the bank chooses a commitment that leaves strictly profitable platform lending. With no fixed entry cost, and because no lending yields zero, a zero-profit entrant is indifferent between entering with zero mass or not lending; the no-entry outcome must be selected explicitly at a tie.

Let $\widehat{\Pi}_p(R_b, I, M_b; \mu) = \sup_{R_p, M_p \neq \varnothing} \Pi_p$ denote the platform's maximum operating profit under a nonempty lending policy. Define Π_b^D as the bank's best profit subject to deterring entry, and Π_b^A as its equilibrium profit under accommodation:

$$\Pi_b^D = \sup_{R_b, I, M_b : \widehat{\Pi}_p \leq 0} \Pi_b^M(R_b, I, M_b).$$

The bank obtains the corresponding bank-only allocation when the entrant chooses nonentry; at a zero-profit tie this requires specifying nonentry as the follower's selection. The bank has an incentive to deter only if $\Pi_b^D \geq \Pi_b^A$.

The decision admits a useful decomposition:

$$\Pi_b^D - \Pi_b^A = (\Pi_b^{M,*} - \Pi_b^A) - (\Pi_b^{M,*} - \Pi_b^D).$$

The first difference measures the recoverable monopoly advantage; the second is the loss in bank-only profit caused by the defensive commitment.

A deterrent rate or screening choice may destroy substantial bank-only profit, even if eliminating the platform restores the bank's exclusive lending opportunities.

At $\mu = 0.10$ under the benchmark $\alpha = 2$ and $c_b = 1$, the unadjusted monopoly optimum is $R_b^M \simeq 1.7522$, $I^M \simeq 0.7861$, and $\Pi_b^{M,*} \simeq 0.2080$. The platform then has strictly positive attainable profit, so entry is not blockaded. The accommodating equilibrium instead yields $\Pi_b^A \simeq 0.2038$. An illustrative aggressive deterrent commitment $R_b = 1.20$, $I = 0.80$ leaves the bank only 0.0077, but it is not the optimal deterrent policy.

A numerical constrained search over bank rates and screening intensity, retaining the exact piecewise platform best response and comparing all bank approval policies, locates a substantially better near-binding deterrent commitment at $R_b \simeq 1.3453$ and $I \simeq 0.8453$. Its bank-only profit is approximately $\Pi_b^D \simeq 0.0662$; the platform's maximum positive-policy return is approximately zero, and nonentry must be chosen at an exact tie. Even this improved deterrent payoff is far below accommodation. The recoverable monopoly advantage is only about 0.0042, against approximately 0.1418 in sacrificed bank-only profit at the deterrent commitment. Thus, in this numerical case, preserving the lending relationship is not worth the distorted rate and screening policy needed to exclude the platform. The search supports the local numerical comparison but is not a global analytical characterization of deterrence for every adoption rate or approval policy. In particular, feasibility at $\mu = 0.10$ does not imply feasibility at higher adoption, when the platform's signal becomes more informative.

B.8 Supporting implications: adoption observability and bank portfolio risk

If adoption were observable and the bank could post R_b^A and R_b^N to adopters and nonadopters, but retained common screening and favorable-signal lending, the bank's objective in the benchmark cell would be

$$(1-\mu)G_M(R_b^N, I) + \mu\big[G_M(R_b^A, I) - a_S\delta\Delta_S^A m_b^S(R_b^A)\big] - C(I),$$

where $G_M(R, I) = \Pi_b^M(R, I) + C(I)$ is the bank's gross monopoly return. Holding I fixed, the nonadopter rate obeys $F_M(R_b^N, I) = 0$, while the adopter rate satisfies the competitive condition without the multiplier μ. This shows which common-price restriction is responsible for the spillover of competitive repricing to nonadopters. It does *not* imply that both rates, or a loan-weighted average, fall. The calibrated constrained exercise at $\mu = 0.50$ gives $R_b^N \simeq 1.752$, $R_b^A \simeq 2.038$ and bank portfolio default frequency about 10.18%, compared with the pooled bank rate 1.836 and default frequency 10.55%. This is a restricted pricing extension, not an equilibrium with unrestricted segment-specific screening and approval policies.

Finally, at unchanged bank choices in the benchmark coverage region, entry displaces $d = \mu a_S\delta\Delta_S$ safe bank loans. The bank's origination masses change from (L_0^S, L_0^R) to $(L_0^S - d, L_0^R)$, a special case of the general relative-displacement formula in Appendix B.10.

The benchmark equilibrium path is computed at 1,001 values of $\mu \in [0.10, 0.90]$ under identical primitives for monopoly and competition. All reported points satisfy the safe-covered/risky-uncovered inequalities. The follower's rate is checked against the exact piecewise pricing cells and all offer policies at each point; independent multistart bank comparisons are available at 21 adoption values. The agreement of analytical and finite-difference derivatives supports the smooth-branch FOCs, but a finite numerical search is not an analytical uniqueness proof. Delayed screening, simultaneous pricing, and screening-signal-contingent price discrimination are excluded from this appendix because they require distinct games

and would not sharpen the maintained benchmark's equilibrium characterization.

B.9 Smooth undercutting and the informational allocation externality

At fixed approval policies within the interior two-offer region, a bank rate decrease of $\varepsilon > 0$ shifts the safe-borrower cutoff by $\theta^S \varepsilon/(2t)$ if the platform rate is fixed. Along a differentiable platform best response, the shift is $\theta^S(1-\rho_p)\varepsilon/(2t) + o(\varepsilon)$. Multiplying by $\mu p \gamma \delta$ gives the first-order mass of safe borrowers won from the platform. This mass converges to zero with ε, unlike the discrete transfer of all jointly approved applicants at a tied bid in Broecker (1990). This smoothness does not exclude follower-policy switches or multiple global best responses at non-interior points.

B.10 Relative displacement, portfolio quality, and data precision

Let $p_S = p$ and $p_R = 1 - p$, and retain the general type-conditional offer probabilities q_b^j, q_p^j introduced above. Define the bank-only mass $L_0^j = p_j q_b^j D_b^j$ at the same bank rate and approval policy as the competitive outcome. The ex ante loan-mass identities imply

$$L_b^j = L_0^j - \mu p_j q_b^j q_p^j \Delta_j = L_0^j(1 - s_j), \qquad s_j = \frac{L_0^j - L_b^j}{L_0^j} = \frac{\mu q_p^j \Delta_j}{D_b^j}, \quad \Delta_j = D_b^j - \widetilde{D}_b^j \geq 0.$$

The proportional displacement s_j is defined for $D_b^j > 0$. Because $0 \leq \widetilde{D}_b^j \leq D_b^j \leq 1$, the bank cannot originate more loans of either true type at unchanged bank decisions following entry. The statement does not rank separately optimized monopoly and competitive bank loan books.

Let $T = L_0^S + L_0^R$ and $Q = L_b^S + L_b^R$. The default-frequency identity $\Omega_b = (1 - \theta^S) +$

$(\theta^S - \theta^R)L_b^R/Q$ gives

$$\begin{aligned}\Omega_b - \Omega_{b,0} &= (\theta^S - \theta^R)\left[\frac{L_0^R(1-s_R)}{Q} - \frac{L_0^R}{T}\right] \\ &= (\theta^S - \theta^R)\frac{L_0^S L_0^R(s_S - s_R)}{TQ}.\end{aligned}$$

This establishes the first part of Proposition 1 for positive type-specific originations.

Under favorable-signal lending $q_p^S = \delta$, $q_p^R = 1 - \delta$, so at fixed (R_b, R_p, I),

$$\frac{\partial L_b^S}{\partial \delta} = -\mu p \gamma \Delta_S \leq 0, \qquad \frac{\partial L_b^R}{\partial \delta} = \mu(1-p)(1-\gamma)\Delta_R \geq 0.$$

As $\theta^S > \theta^R$, differentiation of the risky-origination share yields

$$\frac{\partial \Omega_b}{\partial \delta} = (\theta^S - \theta^R)\frac{L_b^S\, \partial_\delta L_b^R - L_b^R\, \partial_\delta L_b^S}{(L_b^S + L_b^R)^2} \geq 0.$$

The inequality is strict when both types are financed and either Δ_S or Δ_R is positive. This is a *fixed-decision* comparative static, not an assertion that equilibrium risk is monotone in platform precision. For the maintained technology $\delta(\mu;\alpha) = (1+\mu^{1/\alpha})/2$ and $0 < \mu < 1$, one has $\delta_\alpha = -\mu^{1/\alpha}\log\mu/(2\alpha^2) > 0$. Thus the precision result also applies to an increase in α at fixed adoption and lending decisions.

In the benchmark, $\Delta_R = 0$ and $d = \mu p \gamma \delta \Delta_S$, so the general identity reduces to

$$\Omega_b - \Omega_{b,0} = \frac{(\theta^S - \theta^R) d L_0^R}{T(T-d)} \geq 0.$$

The direct diversion term has derivative $\partial_\mu(\mu\delta) = \delta + \mu\delta_\mu$. This separates the platform's reach effect from the additional effect of adoption-driven signal improvement. It is distinct from the total equilibrium derivative, which also includes changes in the two rates and screening.

Full-coverage robustness. The relative-displacement criterion does not require uncovered risky demand. To demonstrate this numerically without relaxing negative-NPV risky projects, set $Y^R = 0.90$ and retain the other benchmark primitives. The previously computed 801-point candidate equilibrium path for $\mu \in [0.10, 0.90]$ has strictly overlapping acceptable offers for both types; selective lending remains optimal on the globally checked points. Bank default frequency rises from approximately 10.38% in its own monopoly to 13.43% at $\mu = 0.90$, with safe loans displaced proportionately more than risky ones. The exact platform policy was checked at every grid point and independent bank global policy comparisons agreed at nine points. These are robustness calculations, not a theorem of global uniqueness.

B.11 Why the conditional competitive bank rate is higher

Consider the strictly interior safe-covered/risky-uncovered cell under favorable-signal lending. Let $a_S = p\gamma$ and $a_R = (1-p)(1-\gamma)$, and write $m_b^j = \theta^j R_b - c_b$. The derivative of monopoly profit with respect to R_b, at fixed I, is

$$F_M(R_b, I) = \sum_{j \in \{S,R\}} a_j \theta^j \left[D_b^j - \frac{m_b^j}{t} \right].$$

At the conditional monopoly optimum, $F_M(R_b^M(I), I) = 0$. If $a_R > 0$, $D_b^R > 0$, and $m_b^R < 0$, the risky term in this condition is strictly positive. Consequently the safe term is negative:

$$D_b^S(R_b^M) < \frac{m_b^S(R_b^M)}{t}.$$

Since $\bar{x}^S = (\bar{x}_b^S + \bar{x}_p^S)/2$, the displacement term under interior demands satisfies

$$\Delta_S = D_b^S - \widetilde{D}_b^S = \frac{D_b^S - \bar{x}_p^S}{2} < \frac{D_b^S}{2} < \frac{m_b^S}{2t},$$

where $\bar{x}_p^S > 0$ follows from the platform-only safe demand being strictly smaller than one. Under nonnegative conditional platform rate pass-through, $\rho_p \geq 0$, this yields

$$\Delta_S - \frac{1+\rho_p}{2t} m_b^S < 0.$$

Differentiating the bank's profit wedge along the platform's best response,

$$\frac{d\Pi_b}{dR_b} = F_M(R_b, I) - \mu a_S \delta \theta^S \left[\Delta_S - \frac{1+\rho_p}{2t} m_b^S \right],$$

shows that the bank's marginal competitive profit is positive at the monopoly conditional rate. Strict concavity of the induced bank pricing objective *within that cell*, and the assumption that both optima are in the cell, imply $R_b^C(I) > R_b^M(I)$. The inequalities do not extend automatically to binding participation thresholds or to changes in approval policy. This is the conditional result asserted by Proposition 2.

B.12 The direct and strategic returns to screening

For the bank's gross monopoly return, write $\Lambda(R_b) = \{pD_b^S m_b^S - (1-p)D_b^R m_b^R\}/2$. With a fixed platform rate, the loan-mass identity implies

$$\frac{\partial(\Pi_b + C)}{\partial I} = \Lambda(R_b) - \frac{\mu p \delta}{2} \Delta_S m_b^S.$$

Because $\gamma'(I) = 1/2$ and Δ_S is independent of I at fixed posted rates, this establishes the fixed-rate direct screening displacement effect discussed in the main text. When the bank anticipates the platform's response, Δ_S also changes through $R_p^*(R_b, I; \mu)$, so

$$C'(I) = \underbrace{\Lambda(R_b)}_{\text{monopoly marginal benefit}} - \underbrace{\frac{\mu p \delta}{2} \Delta_S m_b^S}_{\text{direct displacement}} + \underbrace{\frac{\mu p \gamma \delta \theta^S}{2t} m_b^S \frac{\partial R_p^*}{\partial I}}_{\text{strategic repricing}}.$$

Define the entire right side as $\mathcal{H}(R_b, I, \mu)$. Differentiating the equilibrium screening condition yields

$$[C''(I^*) - \mathcal{H}_I]I^*_\mu = \mathcal{H}_\mu + \mathcal{H}_{R_b}(R^*_b)_\mu,$$

where the partial derivatives of $\mathcal{H}$ include any dependence of the platform's best response on μ and I. The denominator is positive at a strict conditional screening maximum. The turning point occurs where the numerator vanishes; neither the sign of screening's first derivative nor the sign of its second derivative is a primitive implication of the data technology.

The benchmark equilibrium evaluation of the three right-hand-side terms confirms the interpretation in the main text: as μ approaches the high-adoption range, the safe-demand overlap shrinks enough that the direct displacement term becomes smaller in absolute value, while the strategic repricing contribution grows. The resulting screening path has an interior minimum. These observations are numerical properties of the maintained benchmark, not an analytic assertion about all parameter values.

C Adoption sorting and the distribution of lender convenience

The benchmark assumes a uniform unconditional convenience characteristic $X \sim U[0, 1]$ and independent platform adoption. A more general environment allows the adoption decision to be correlated with lender convenience while preserving the distribution of borrower types and the platform's aggregate adoption rate. Let $U \sim U[0, 1]$ index a latent adoption propensity, with $A = \mathbf{1}\{U \leq \mu\}$. Assume the borrower credit type $j \in \{S, R\}$ is independent of (X, U), and define their joint CDF (a copula, since both marginal distributions are uniform) as

$$C(x, u) = \Pr(X \leq x, U \leq u), \qquad (x, u) \in [0, 1]^2. \tag{C.1}$$

We require that C have no point masses and be continuously differentiable at the interior cutoffs used below, with a nonnegative joint density. The benchmark is the independent copula $C_0(x,u) = xu$. At every $0 < \mu < 1$, the adopter and non-adopter conditional CDFs are

$$F_A(x;\mu) = \frac{C(x,\mu)}{\mu}, \qquad F_N(x;\mu) = \frac{x - C(x,\mu)}{1-\mu}, \quad \mu F_A + (1-\mu)F_N = x. \tag{C.2}$$

Thus the unconditional distribution of X stays uniform as the platform grows, and adoption is nested: users with $U \leq \mu$ remain adopters when μ increases. If adopters are weakly more platform-oriented than non-adopters in the sense of first-order stochastic dominance, then $F_A(x;\mu) \leq F_N(x;\mu)$, equivalently $C(x,\mu) \leq \mu x$. The independence case satisfies equality. Neither this ordering nor the marginal uniformity assumptions require a particular parametric CDF.

For a conventional smooth example within this class, let

$$C_\rho(x,u) = \Phi_2\big(\Phi^{-1}(x), \Phi^{-1}(u); \rho\big), \qquad -1 < \rho < 1,$$

where Φ_2 is the standard bivariate normal CDF with correlation ρ. For $\rho = 0$, $C_0(x,u) = xu$ and both conditional distributions are uniform. A negative ρ associates low adoption rank U with high platform convenience X, thereby sorting adopters toward the platform. This Gaussian-copula family serves only to demonstrate that the admissible class contains economically meaningful, non-independent distributions; no new equilibrium results rely on a chosen ρ.

C.1 Origination masses under correlated adoption

Conditional demands remain determined by borrower utility. With raw bank and platform acceptance cutoffs $\bar{x}_b^j, \bar{x}_p^j$ and the lender-indifference cutoff $\bar{x}^j$ as defined in the model, define

the interval of borrowers diverted from the bank when both lenders extend credit:

$$\ell_j = \max\{0, \bar{x}_p^j, \bar{x}^j\}, \qquad h_j = \min\{1, \bar{x}_b^j\},$$

$$G_j(\mu) = \begin{cases} C(h_j, \mu) - C(\ell_j, \mu), & h_j > \ell_j, \\ 0, & h_j \le \ell_j. \end{cases} \tag{C.3}$$

In the strictly interior covered region this reduces to $G_j = C(\bar{x}_b^j, \mu) - C(\bar{x}^j, \mu)$. Under independence, $G_j = \mu\Delta_j$, with $\Delta_j = D_b^j - \widetilde{D}_b^j$; for an uncovered type the interval is empty and $G_j = 0$.

Let $p_S = p$, $p_R = 1 - p$, and retain the type-conditional approval probabilities q_b^j, q_p^j defined in Appendix B. Because true type is independent of (X, U), and because the bank may serve all borrowers, its bank-only origination mass at unchanged decisions remains $L_0^j = p_j q_b^j D_b^j$. Its competitive mass is exactly

$$L_b^j = p_j q_b^j \big[D_b^j - q_p^j G_j(\mu)\big]. \tag{C.4}$$

To obtain the platform's mass, define $v_j = [\bar{x}_p^j]_0^1$ and the interval of adopters who accept the platform alone but prefer the bank when two offers are available:

$$a_j = \max\{0, \bar{x}_p^j\}, \quad b_j = \min\{1, \bar{x}_b^j, \bar{x}^j\}, \quad H_j(\mu) = \begin{cases} C(b_j, \mu) - C(a_j, \mu), & b_j > a_j, \\ 0, & b_j \le a_j. \end{cases}$$

Then

$$L_p^j = p_j q_p^j \big[\mu - C(v_j, \mu) - q_b^j H_j(\mu)\big]. \tag{C.5}$$

These equations integrate the joint probabilities of true type, adoption, approval and lender choice. Ex ante profits remain $\Pi_b = \sum_j L_b^j(\theta^j R_b - c_b) - C(I)$ and $\Pi_p = \sum_j L_p^j(\theta^j R_p - c_p)$; no posterior is multiplied into an already type-specific loan mass. Bank application demand,

$p_j D_b^j$, is unchanged because the *unconditional* distribution of X is still uniform. Platform application demand is instead $p_j[\mu - C(v_j, \mu)]$, so its applicant priors and optimal pricing generally change.

Lemma 2 (Relative displacement with sorted adoption)**.** *At unchanged posted rates, screening and approval policies, suppose $D_b^S, D_b^R > 0$ and the bank originates positive loans of both types. Let $s_j \equiv q_p^j G_j(\mu)/D_b^j$. Then $L_b^j = L_0^j(1 - s_j)$ and the bank's expected default frequency increases relative to bank-only lending if and only if $s_S > s_R$. In a favorable-signal equilibrium, an increase in platform accuracy δ holding all other decisions fixed weakly reduces L_b^S and weakly increases L_b^R, and therefore weakly increases the bank's expected default frequency. The statements include independent adoption as the special case $C(x, u) = xu$.*

Proof. Equation (C.4) immediately gives $L_b^j = L_0^j(1-s_j)$. Let $T = L_0^S + L_0^R$ and $Q = L_b^S + L_b^R$. The definition $\Omega_b = [(1 - \theta^S)L_b^S + (1 - \theta^R)L_b^R]/Q$ gives

$$\Omega_b - \Omega_{b,0} = (\theta^S - \theta^R)\frac{L_0^S L_0^R(s_S - s_R)}{TQ},$$

which proves the sign claim. For favorable-signal approval, $q_p^S = \delta$ and $q_p^R = 1 - \delta$, so $\partial_\delta L_b^S = -p\gamma G_S \leq 0$ and $\partial_\delta L_b^R = (1 - p)(1 - \gamma)G_R \geq 0$. More explicitly, $\partial_\delta \Omega_b = (\theta^S - \theta^R)[L_b^S \partial_\delta L_b^R - L_b^R \partial_\delta L_b^S]/(L_b^S + L_b^R)^2 \geq 0$, proving the remaining claim. □

C.2 Reach, information, and marginal price competition

In the interior safe-covered region the bank's safe-loan diversion at fixed lender decisions is

$$d_S = p\gamma\delta(\mu; \alpha)G_S(\mu), \qquad G_S(\mu) = C(\bar{x}_b^S, \mu) - C(\bar{x}^S, \mu).$$

Along a fixed adoption-ranking copula, and holding the cutoffs fixed,

$$\frac{\partial d_S}{\partial \mu} = p\gamma \left[\underbrace{\delta_\mu G_S}_{\text{information improvement}} + \underbrace{\delta\{C_u(\bar{x}_b^S, \mu) - C_u(\bar{x}^S, \mu)\}}_{\text{new adopters in the contestable interval}} \right] \geq 0. \tag{C.6}$$

The second term is nonnegative since $C_u(h, \mu) - C_u(\ell, \mu)$ is the conditional probability that a marginal adopter lies between the two cutoffs. Under independence, $G_S = \mu\Delta_S$ and the expression reduces to $p\gamma\Delta_S(\delta + \mu\delta_\mu)$. In particular, a larger platform need not displace the same share of safe bank loans as an equally large platform with uniformly distributed users.

If F_A has a continuous density $f_A(x; \mu) = C_x(x, \mu)/\mu$, an infinitesimal bank-rate cut $\varepsilon > 0$ along a differentiable platform best response wins a mass of jointly approved safe adopters equal to

$$\mu p\gamma\delta \, f_A(\bar{x}^S; \mu) \frac{\theta^S(1 - \rho_p)}{2t}\varepsilon + o(\varepsilon),$$

provided the indifference cutoff stays in the strictly covered interior. Local price competition depends on the *density of adopters at the contestable margin*, not merely their total mass. First-order stochastic dominance of adopters' X over nonadopters' X does not generally order G_S or $f_A(\bar{x}^S)$ relative to the independence benchmark: interval probabilities and point densities depend on the shape of the CDF, not only its first-order ranking.

Although the absolute continuity assumption prevents an infinitesimal cut from transferring a positive mass of borrowers at once, it does not ensure that the platform's profit remains quadratic or that its best response remains unique. With sorted adoption both lenders' equilibrium problems must therefore be re-solved using (C.4)–(C.5); the benchmark's affine follower best response and interior existence arguments cannot be reused mechanically. This extension establishes the robustness of the *conditional* displacement logic, not a newly computed equilibrium path under correlated adoption.

D Platform information and funding-cost comparative statics

D.1 Proof of Proposition 3

For favorable-signal lending, let $\Delta_j = D_b^j - \widetilde{D}_b^j \geq 0$ and $m_b^j = \theta^j R_b - c_b$. The ex ante bank loan masses in equations (5.1) and (5.2) can be written without additional posterior probabilities as

$$L_b^S = L_0^S - \mu p\gamma\delta\Delta_S, \qquad L_b^R = L_0^R - \mu(1-p)(1-\gamma)(1-\delta)\Delta_R,$$

where L_0^j is evaluated at the same bank rate and screening as under competition. Holding R_b, R_p, I fixed, $\delta_\alpha = -\mu^{1/\alpha}\log\mu/(2\alpha^2) > 0$ and

$$\partial_\alpha L_b^S = -\mu p\gamma\Delta_S\delta_\alpha, \qquad \partial_\alpha L_b^R = \mu(1-p)(1-\gamma)\Delta_R\delta_\alpha.$$

With $\Omega_b = (1-\theta^S) + (\theta^S - \theta^R)L_b^R/(L_b^S + L_b^R)$, differentiation gives

$$\left.\frac{\partial\Omega_b}{\partial\alpha}\right|_{R_b,R_p,I} = \frac{(\theta^S-\theta^R)\mu\delta_\alpha}{(L_b^S+L_b^R)^2}\left[p\gamma\Delta_S L_b^R + (1-p)(1-\gamma)\Delta_R L_b^S\right] \geq 0. \tag{D.1}$$

The inequality is strict when both types are originated and at least one of Δ_S, Δ_R is positive. Consequently the result does not rely on an uncovered risky market. The bank's profit derivative is

$$\left.\frac{\partial\Pi_b}{\partial\alpha}\right|_{R_b,R_p,I} = -\mu\delta_\alpha\left[p\gamma\Delta_S m_b^S - (1-p)(1-\gamma)\Delta_R m_b^R\right] \leq 0$$

when $m_b^S \geq 0$ and $m_b^R \leq 0$. Since $\gamma'(I) = 1/2$ and the rate-dependent quantities are held fixed, its gross marginal screening return satisfies

$$\left.\frac{\partial}{\partial\alpha}\left(\frac{\partial\Pi_b}{\partial I} + C'(I)\right)\right|_{R_b,R_p} = -\frac{\mu\delta_\alpha}{2}\left[p\Delta_S m_b^S - (1-p)\Delta_R m_b^R\right] \leq 0. \tag{D.2}$$

In the benchmark's risky-uncovered case, $\Delta_R = 0$, reducing (D.1) to (6.1). The proof does not assume that the derivatives retain these signs after lenders reoptimize. □

D.2 Interior pass-through and the safe-coverage frontier

Lemma 3 (Conditional funding-cost pass-through)**.** *Within the strictly interior safe-covered/risky-uncovered region, the bank's conditional optimal rate increases with c_b when $c_p = \psi c_b$, for fixed screening, adoption and information quality.*

Proof. The platform's interior response is affine, $R_p = a_0 + \eta_p c_p + \rho_p R_b$, with $\eta_p > 0$ and $0 < \rho_p < 1$. At fixed I, μ, α, bank loan masses can then be written $L_b^j = A_j - K_j R_b$, $K_j > 0$. The risky-loan intercept does not vary with funding costs, while $\partial A_S / \partial c_b = \psi p \gamma \mu \delta \theta^S \eta_p / (2t) > 0$. The bank rate solves

$$R_b^C(I) = \frac{\theta^S A_S + \theta^R A_R + c_b(K_S + K_R)}{2(\theta^S K_S + \theta^R K_R)}.$$

The slope coefficients K_j are independent of funding costs in this cell, so

$$\left.\frac{\partial R_b^C}{\partial c_b}\right|_I = \frac{K_S + K_R + \psi p \gamma \mu \delta (\theta^S)^2 \eta_p / (2t)}{2(\theta^S K_S + \theta^R K_R)} > 0.$$

The argument does not apply after a participation or approval-policy boundary is reached.

For interior participation thresholds, the share of safe bank-only demand lost when both offers are acceptable is

$$\Delta_S = \left[\frac{2Y^S - \theta^S(R_b + R_p) - t}{2t}\right]_+,$$

within the relevant pricing cell. The bracketed formula is not meant to replace the general truncated-demand definition outside this cell. The coverage frontier is $\theta^S(R_b + R_p) = 2Y^S - t$. At the frontier, profit is continuous but the marginal return to a rate change is determined by its one-sided derivatives. The exact follower optimum and the bank's other lending policies must still be compared.

The supplied numerical exercise traces 2,001 adoption values in $[0.10, 0.90]$ for each of eight combinations of $\alpha \in \{1.25, 1.50, 1.75, 2\}$ and $c_b \in \{1, 1.1\}$, holding $c_p = 1.1c_b$. The platform's piecewise best response and approval policy are checked at all 16,008 points; independently optimized bank-policy checks are available at selected locations. At $c_b = 1$, all traced paths remain strictly interior. At $c_b = 1.1$, the safe-coverage frontier first binds at $\mu \simeq 0.7952, 0.7916, 0.7884, 0.7864$, respectively. These are verified numerical equilibrium candidates at grid points, not an analytical uniqueness theorem for every adoption value.

D.3 Additional figures and numerical comparisons

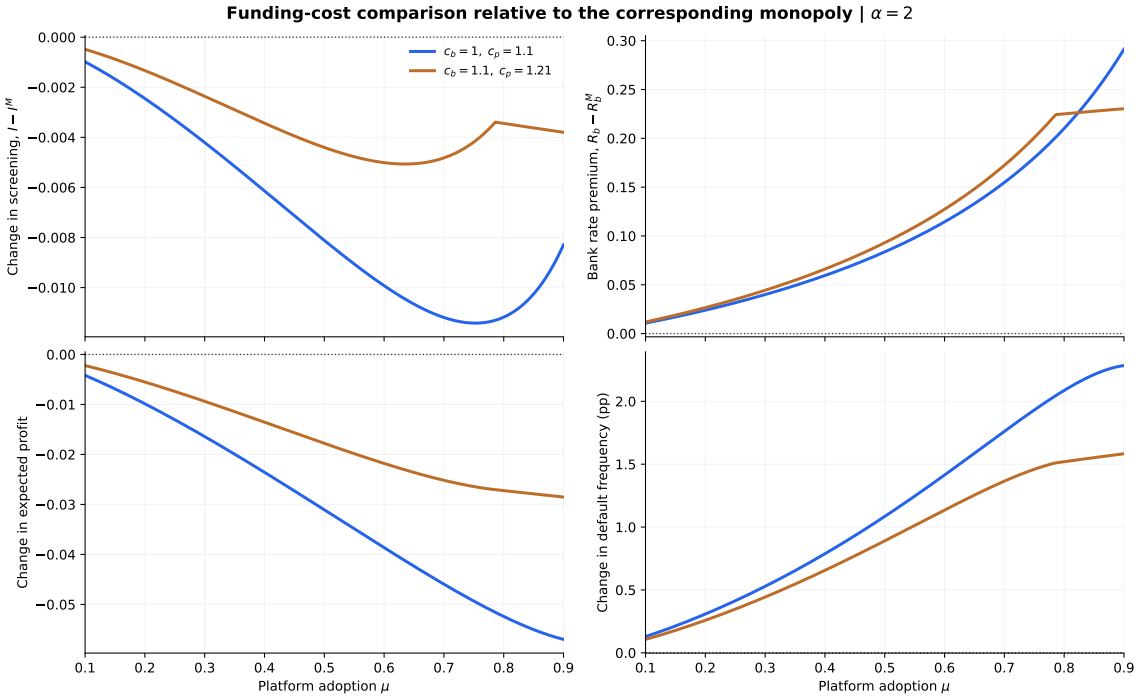


Figure 10: **Funding-cost responses relative to monopoly** ($\alpha = 2$). Differences are computed relative to the reoptimized monopoly under each respective funding cost, avoiding comparisons with different primitives.

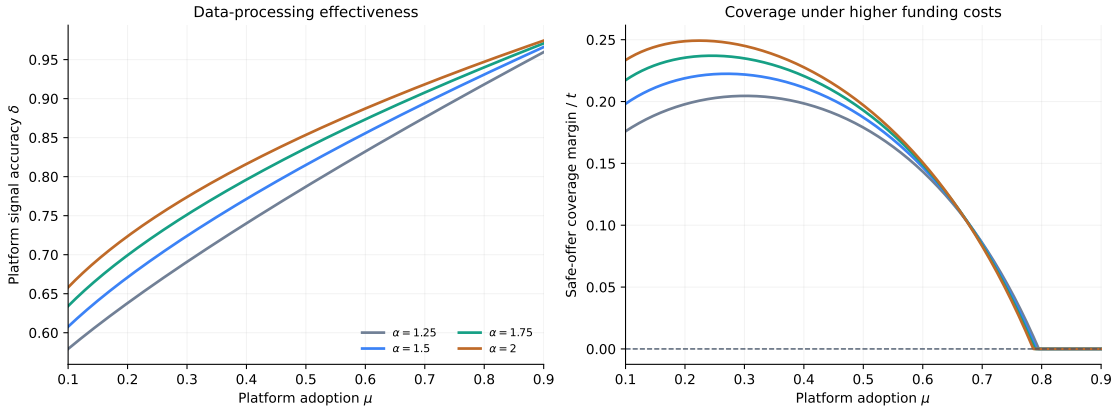


Figure 11: **Information precision and acceptable-offer overlap.** Platform information quality and the safe-market coverage frontier across adoption levels and funding-cost configurations.

E Efficiency and welfare accounting

Productive efficiency. The social return of a type-j loan made by intermediary ℓ is $Y^j - c_\ell$. The model assumes $Y^S > c_p > c_b > Y^R$ and no aggregate bank lending-capacity limit. A planner who observes true borrower types therefore lends only to safe types, uses the bank, and incurs no screening cost. Thus $W^{P,FB} = p(Y^S - c_b)$. Subtracting equilibrium productive surplus in (7.1) and collecting terms by type yields the decomposition in (7.2). In particular, the same expected project payoff Y^j appears in the private loan margins and the social surplus; failure is already reflected in expected output.

Borrower convenience and total welfare. For the favorable-signal policies, let $p_S = p, p_R = 1 - p$ and denote the probability of approval conditional on true type by q_b^j, q_p^j, as in Appendix B. Under the uniform convenience distribution, the ex ante convenience cost

incurred by borrowers who obtain bank-only, platform-only, and competing offers is

$$\mathcal{D} = \frac{t}{2} \sum_{j \in \{S,R\}} p_j \Big\{ q_b^j (1 - \mu q_p^j)(D_b^j)^2 + \mu q_p^j (1 - q_b^j)(D_p^j)^2 + \mu q_b^j q_p^j \big[(\widetilde{D}_b^j)^2 + (\widetilde{D}_p^j)^2 \big] \Big\}. \tag{E.1}$$

For a bank-only offer, for example, a financed borrower has $x_i \in [0, D_b^j]$, yielding $t \int_0^{D_b^j} x \, dx = t(D_b^j)^2/2$. Platform-only offers have the symmetric interval at the upper end of $[0, 1]$. When both offers are available, the bank and platform financing intervals do not overlap; their contributions are the squares of the two conditional demand lengths. The formula applies with the truncated demands used in the main model.

Borrower surplus equals

$$CS = \sum_{j \in \{S,R\}} \big[L_b^j (Y^j - \theta^j R_b) + L_p^j (Y^j - \theta^j R_p) \big] - \mathcal{D}.$$

Adding expected lender profits gives

$$CS + \Pi_b + \Pi_p = \sum_j \big[L_b^j (Y^j - c_b) + L_p^j (Y^j - c_p) \big] - C(I) - \mathcal{D} = W. \tag{E.2}$$

Expected repayments cancel; neither the screening expenditure nor the financing losses associated with default are counted twice. This identity presumes funding costs represent real resources, not purely financial transfers.

Efficient lender assignment. When convenience costs are real, a safe platform adopter with both lenders available should be assigned to the bank when $Y^S - c_b - tx \geq Y^S - c_p - t(1-x)$, i.e. $x \leq x^{\text{eff}} = \frac{1}{2} + (c_p - c_b)/(2t)$. At the benchmark parameters all safe projects are socially productive regardless of convenience, and the full-information total-surplus benchmark is

$$W^{FB}(\mu) = p \left(Y^S - c_b - \frac{t}{2} \right) + \mu p t (1 - x^{\text{eff}})^2.$$

For $p = 1/2$, $Y^S = 2.3$, $c_b = 1$, $c_p = 1.1$, and $t = 0.75$, this is $W^{FB}(\mu) \simeq 0.4625 + 0.07042\mu$. The increasing first-best is due solely to the possibility of assigning safe adopters with a high x to a more convenient lending channel. This result assumes that introducing a platform option does not itself consume resources.

Creation, diversion, and the incumbent response. At competitive bank decisions, hypothetical bank-only origination is $\widehat{L}_b^j = p_j q_b^j D_b^j$. Define $T^j = \widehat{L}_b^j - L_b^j \geq 0$ as loans diverted from the bank and $N^j = L_p^j - T^j \geq 0$ as newly funded projects, all evaluated at those same bank decisions. The difference in productive surplus relative to the *reoptimized* bank-only equilibrium is then exactly

$$\begin{aligned} W^{P,C} - W^{P,M} = & \sum_j (\widehat{L}_b^j - L_0^{j,M})(Y^j - c_b) + \sum_j N^j (Y^j - c_p) \\ & - \sum_j T^j (c_p - c_b) + C(I^M) - C(I^C). \end{aligned}$$

The first term captures how the bank's own choices change its hypothetical lending portfolio; the second and third distinguish new platform credit from diverted bank lending. The identity follows by substituting $L_b^j = \widehat{L}_b^j - T^j$ and $L_p^j = N^j + T^j$. Since the hypothetical bank-only masses are evaluated at competitive decisions, this accounting identity is not a second equilibrium in which the bank reoptimizes after platform removal.

Numerical verification. The four components of (7.2) add to the calculated first-best gap at each of the 2,001 stored adoption values. The maximum absolute reconciliation error is below 3×10^{-16}. Net productive surplus reaches a minimum at $\mu = 0.1692$ and first exceeds the reoptimized bank-only benchmark at $\mu = 0.3472$ on the saved grid. Total welfare $W = W^P - \mathcal{D}$ increases along that same range. These are properties of the reported equilibrium branch on $[0.1, 0.9]$, not global comparative-static statements over all adoption values or market-coverage regimes.