Data Ownership, Data Production, and Lending Market Competition

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Abstract

When can borrower ownership of bank-produced data improve allocative efficiency in credit markets? We study an incumbent bank that strategically chooses portable-data production before a fintech with a portable-data processing advantage decides whether to enter the market. The bank's non-portable-data endowment and the fintech's analytical efficiency determine whether the bank balances improved screening against stronger competition or chooses a portable-data level that creates enough informational asymmetry to deter entry. Equilibrium portable-data production can be nonmonotonic and discontinuous in both primitives. Borrower ownership improves allocative efficiency only if it induces entry and the resulting diversification benefit outweighs the loss of precision.

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1 Introduction

Data have become a central input into credit allocation. Banks, fintech lenders, and other financial intermediaries increasingly process borrower data to generate information used to screen applicants, price loans, and manage default risk. Control over borrower data can therefore be a source of market power. An incumbent lender that understands its customers better than potential rivals can use that informational advantage to retain borrowers, deter entry, and shape the allocation of credit. As financial data become easier to store, process, and transmit, a central policy question is no longer only who can use borrower data, but who controls them and who can transfer them.

A growing set of policies shifts control rights over financial data from lenders to borrowers. Open banking, consumer data portability regimes such as Australia's Consumer Data Right, Brazil's Open Finance framework, and broader open-finance reforms all give borrowers greater ability to move their financial histories across financial institutions. The standard rationale is straightforward. If borrower data are locked inside incumbent lenders, entrants face an informational disadvantage. Letting borrowers transfer their data should reduce switching frictions, intensify competition, expand credit access, and improve credit allocation. These policies differ in institutional detail, but they share a common premise: more transferable borrower data should make lending markets more contestable.

This paper studies how data ownership reshapes a strategic margin: the incumbent's endogenous production of transferable borrower data. Data-rights policies affect not only the use of existing data, but also the production of data. In credit markets, useful borrower data are not simply waiting to be shared across lenders. Intermediaries decide what observations to collect and codify, how to construct their internal records, and to what extent to convert repeated customer interactions into borrower-level screening inputs. This production margin is especially important in dynamic banking relationships. A bank may observe a future borrower long before she applies for credit, for example through a custodial account, a student account, a household relationship, or accounts linked to her parents. The bank can decide whether to record this history in a standardized form that later serves as an input into credit screening. Hence, unlike works that take the stock of transferable borrower data as given and study how access affects competition across

lenders (He et al. 2023; Goldstein et al. 2025), we let the incumbent choose how much portable data to produce. Once those data can be transferred to rivals, the bank no longer fully appropriates the returns from producing them. Giving entrants access to borrower data therefore need not make the lending market contestable.

Against this background, we ask three questions. How do the incumbent's non-portable-data advantage and a fintech entrant's analytical efficiency in converting portable borrower data into screening information determine the production of portable data? When does the resulting information environment allow fintech entry rather than enable incumbent deterrence? Given endogenous production and market structure, when does shifting data control to borrowers improve credit allocation?

Our mechanism is a feedback between data production and entry. Data ownership determines whether portable data produced by the bank also become screening inputs for the fintech. Conditional on access, the bank's non-portable-data endowment and the fintech's analytical efficiency map each production choice into a pair of signal precisions. Because both lenders' loan values depend on the same repayment outcome, lending competition is a common-value auction: winning suggests that the rival observed less favorable information, exposing the less-informed lender to a winner's curse. When the bank is sufficiently better informed, this winner's curse drives the fintech's gross entry payoff to zero, so any positive entry cost deters entry. Anticipating this response, the bank chooses the largest portable-data production consistent with deterrence when deterrence is feasible; otherwise, it accommodates entry and balances its own screening gain against the competitive cost of improving the fintech's signal.

We capture lenders' competing informational advantages with two primitives. The first is the incumbent's endowment of non-portable data: relationship-specific or proprietary inputs whose value depends on the incumbent's internal linkages, historical interpretation, or broader customer relationships. The second is the fintech entrant's analytical efficiency, which governs how precisely it can screen a borrower from a given stock of portable data. Portable data are standardized, codified borrower records that can serve as screening inputs for multiple lenders with borrower authorization, such as transaction histories, repayment records, account information, and digital footprints. In the example above, a young borrower can later share her own account history with a new lender, but not the incumbent's relationship-specific records linking her to household and parental

accounts. Portability thus makes one set of screening inputs contestable while leaving the other proprietary. The same stock of portable data can therefore generate signals of different precision across lenders.

We formalize these forces in a dynamic model. An incumbent bank endowed with non-portable borrower data first chooses how much portable data to produce, anticipating the fintech's access and entry response. The ownership regime determines access to the resulting data. Under lender ownership, the bank retains exclusive access to the portable data it produces, leaving the fintech with no borrower-specific information beyond the prior. Under borrower ownership, the borrower can transfer these data to the fintech when shopping for credit. After observing the bank's production choice and the data it would receive, the fintech decides whether to enter. At the lending stage, the bank forms a private signal from its portable and non-portable data, while an entering fintech forms a signal from the transferred portable data. Under borrower ownership, when the stock of portable data is sufficiently large, the fintech's analytical advantage makes its signal more precise than the bank's, even though the bank can be better informed at lower production levels. Conditional on entry, the lenders submit interest-rate offers, and the borrower accepts the lower offer. Data production determines screening precision, while fintech entry determines market structure; together, they shape credit allocation and welfare.

We solve the model by backward induction. The lending subgame maps each pair of signal precisions into continuation payoffs. These payoffs determine fintech entry and thereby turn the technological path through precision space into the bank's portable-data production problem.

The signal technology maps each feasible stock of portable data into a pair of lender precisions, tracing a path through precision space. Whether the bank can deter entry depends on whether some choice along this path makes the fintech's winner's curse severe enough to eliminate its expected profit from entry. The bank's non-portable-data endowment and the fintech's analytical efficiency jointly determine this deterrence possibility. Richer non-portable data make deterrence easier by improving only the bank's signal, whereas greater fintech efficiency reduces it by raising the fintech's precision for any given portable-data stock. When the bank's non-portable-data advantage is limited relative to the fintech's analytical efficiency, no portable-data choice makes the bank suffi-

ciently better informed, so entry must be accommodated. When the bank has sufficiently rich non-portable data relative to the fintech's efficiency, some portable-data choice generates enough asymmetry to deter entry.

We next characterize equilibrium portable-data production. Under lender ownership, the bank retains exclusive access to the portable data it produces so the bank chooses the maximum amount. This outcome provides the benchmark for assessing production under borrower ownership. Under borrower ownership, portable data also improve the fintech's screening, so the bank anticipates the entry response when choosing production. If deterrence is infeasible, the bank balances the benefit of a more precise signal against the cost of strengthening the fintech. If deterrence is feasible, the deterrence-inducing choices form a nonempty set. At the threshold of feasibility, this set can collapse to a single tangency point; away from the threshold, it is an interval. Too little production leaves the bank insufficiently better informed to keep the fintech out, whereas too much gives the fintech a signal precise enough to enter profitably. The bank chooses the set's upper endpoint—the largest stock consistent with keeping the fintech out.

These entry regimes also govern how equilibrium portable-data production responds to the two screening primitives. When the bank must accommodate entry, richer non-portable data reduce optimal portable-data production under our weak-substitutability condition, which requires the marginal precision contribution of portable data not to increase with the bank's non-portable-data endowment. Richer non-portable data lower the bank's marginal screening benefit from producing portable data and make the informational rent lost by strengthening the fintech more costly. The two data types are therefore substitutes in the bank's equilibrium production choice under accommodation. Once the endowment reaches the threshold at which deterrence first becomes feasible, production jumps down to the newly feasible deterrence point. Beyond that threshold, richer non-portable data relax the deterrence constraint, allowing the bank to produce more portable data while keeping the fintech out. The two data types thus become complements in the bank's equilibrium production choice under deterrence.

Fintech efficiency has a different but also nonmonotonic effect on portable-data production. Within either entry regime, greater fintech efficiency reduces production—by tightening the deterrence constraint when entry is deterred and by increasing the competitive cost of production when entry is accommodated. When greater fintech efficiency

makes deterrence infeasible, however, production jumps upward because the bank no longer restricts portable data to preserve monopoly; it then declines again as fintech efficiency increases further.

Finally, taking lender ownership with an incumbent monopoly as the benchmark, we evaluate competition and allocative efficiency under a shift to borrower ownership. If entry remains deterred, the bank remains the sole lender but produces less portable data than under lender ownership. Its screening becomes less precise, and allocative efficiency falls. A nominally pro-competition reform can therefore preserve monopoly while degrading credit allocation.

If borrower ownership induces entry, the policy adds a second, conditionally independent screening signal but also reduces the bank's data production. The welfare comparison therefore pits more diversified screening by two less-informed lenders against more precise screening by one monopoly lender. Borrower ownership improves allocative efficiency only when the benefit of the additional signal dominates the endogenous loss in screening precision. It can expand credit while reducing allocative efficiency when additional lending reflects noisier screening rather than better capital allocation. Data rights must therefore be evaluated after jointly solving for data production and entry.

We extend the analysis in two directions. First, we replace the baseline scale choice with a composition choice over a fixed stock of raw borrower data. The baseline model is best read as applying to future borrowers, for whom portable data have not yet been produced. For existing borrowers, a bank may instead choose what share of its existing raw data to codify into portable screening inputs. This extension preserves the region-based characterization: the bank may choose an all-non-portable, all-portable, or interior share when deterrence is infeasible and chooses the largest share consistent with deterrence when deterrence is feasible. In the logistic illustration, the optimal portable share falls as the total data stock grows because retaining data in non-portable form strengthens the bank's signal.

Second, we allow for multiple symmetric potential fintech entrants. Under the explicit path-wide condition that no feasible data choice can support more than one fintech, either one fintech enters or none does, exactly as in the baseline. The bank's equilibrium data-production problem is therefore unchanged under this condition.

The paper contributes first to the literature on data ownership and the economics of

data. Existing works emphasize that data are nonrival, generate externalities, and can create market power (Jones and Tonetti 2020; Bergemann et al. 2022; Bian et al. 2025). In credit markets, recent studies examine how borrower access to financial data affects entry, pricing, and selection (He et al. 2023; Babina et al. 2025; Nam 2023; Agur et al. 2025; Goldstein et al. 2025). We study a different, ex ante margin: before fintech entry, the incumbent chooses how extensively to codify borrower records as portable data, knowing that these data improve its own screening but, under borrower ownership, also sharpen the fintech's signal. The interaction among portable-data production, relative signal precision, and the lending winner's curse determines whether data portability induces entry or entry deterrence. Open banking is one application of this mechanism, but the mechanism applies more broadly to any regime that shifts control over transferable financial data from firms to customers.

Second, the paper contributes to the literature on financial intermediation and lending competition. A large literature studies how proprietary borrower information gives incumbent lenders market power and shapes credit allocation (Pagano and Jappelli 1993; Hauswald and Marquez 2006; Karapetyan and Stacescu 2014). Recent works study competition between banks and fintech lenders and show that new screening technologies can substitute for or complement traditional bank lending (Tang 2019; Beaumont et al. 2025; Serfes et al. 2025; Huang 2025; Hu and Zryumov 2026). We show that the lending winner's curse maps relative signal precision into entry and market structure. The distinction between portable and non-portable data is therefore central to the effect of data rights. A portability regime can make one set of borrower data transferable while leaving another set proprietary. Because lenders process these data into signals of different precision, the interaction between the two data types determines whether portability produces entry, preserves incumbent market power, or worsens capital allocation.

Third, the paper contributes to the literature on endogenous information acquisition and information production. Models of information acquisition study how agents choose signal precision when information is costly or strategically valuable (Veldkamp 2011; Ichihashi 2021; Acemoglu et al. 2022). In banking, this question is closely related to the distinction between hard, transferable information and soft, relationship-specific information (Liberti and Petersen 2019; Del Gaudio et al. 2020; Begenau et al. 2018; He et al. 2024). We provide a tractable framework in which an incumbent chooses portable-data produc-

tion before fintech entry and lending competition in a common-value credit market. The key methodological step is to recast that choice as the choice of a precision pair along a feasible curve in the signal-precision space. Separating the common-value bidding game in precision space from the technology that maps data stocks into precisions turns the joint production-and-entry problem into a constrained optimization: entry, deterrence, and the associated production jumps are read off the curve's contact with the regional boundaries. The same geometry extends to other settings in which an incumbent chooses information before entry into a common-value auction.

2 Data Production, Entry, and Lending Competition

Our model has two potential lenders, an incumbent bank and a fintech entrant, and four periods, indexed by $t \in \{1, 2, 3, 4\}$. The data-ownership regime is fixed before the game begins and is common knowledge. At $t = 1$, the bank, which is endowed with an exogenous amount of non-portable data about the borrower's period-4 cash flow, chooses how much portable data to produce. At $t = 2$, after observing the amount of portable data produced, the fintech decides whether to enter. At $t = 3$, each active lender processes the data available to it and privately observes the resulting screening signal. The active lenders then simultaneously submit loan offers, and the borrower accepts the offer with the lower interest rate. At $t = 4$, the project's cash flow is realized and payoffs are determined.

Borrower. All agents are risk-neutral, there is no discounting, and outside options are normalized to zero. The borrower seeks to raise \$1 to finance a project. If funded, the project yields cash flow $X \in \{R, 0\}$ in period 4, where $R > 1$ corresponds to success and 0 to failure. We refer to a borrower with $X = R$ as an H-borrower and to a borrower with $X = 0$ as an L-borrower. All agents share a common prior $\Pr(X = R) = \theta \in (0, 1)$. We assume that the project has a positive ex-ante net present value, $\theta R - 1 > 0$. The borrower has limited liability. A lender advances \$1 and, at interest rate r, receives $1 + r$ if the project succeeds and zero if it fails.

The prior summarizes all public information about X. In particular, the borrower has no private information about X beyond the prior, so the borrower's actions have

no signaling role. We therefore abstract from borrower signaling to focus on how data ownership affects lenders' information production and competition.[1]

After receiving loan offers at $t = 3$, the borrower accepts the offer with the lower interest rate. If both lenders offer the same finite rate, the borrower chooses the lender with the more precise signal technology; if their precisions are equal, the borrower chooses the bank. If neither lender submits a finite offer, the project is not funded.[2] This rule completes the borrower's strategy for every pair of lender signal precisions.

Lenders and data. The bank and, upon entry, the fintech can provide the same lending service, but they differ in their access to data and in how they process those data. The bank is endowed with $K \in [\underline{K}, \overline{K}]$ units of non-portable data about the borrower's period-4 cash flow, where $\underline{K} > 0$. The amount K is common knowledge, but the contents of these data are private to the bank. Because the data are relationship-specific and cannot be transferred fully to a rival lender, they remain proprietary to the bank under either ownership regime.

In addition, the bank can produce portable data, which are codified, transferable, and machine-readable. At $t = 1$, the bank chooses the amount of portable data to produce, $I \in [0, \overline{M}]$, and we assume that it always retains access to them.[3] Thus, portable-data production measures the extent to which the bank codifies borrower records and interactions into transferable screening inputs. Here and throughout, I denotes a quantity of data, not information.

The ownership regime determines the fintech's access to these portable data. Under lender ownership, the bank retains exclusive control over the portable data it produces. Under borrower ownership, the bank retains access, but the borrower can direct the data to an entrant. We model this transfer as automatic and costless conditional on fintech entry, thereby abstracting from a separate borrower-authorization decision. Under neither

[1] Borrowers' endogenous decisions to participate in open banking are studied by He et al. (2023).

[2] This tie-breaking rule is in the spirit of Maskin and Riley (2000). As we show below, the bank's equilibrium portable-data choice keeps its signal at least as precise as the fintech's. Thus, the rule can also be interpreted as capturing reduced-form switching costs that favor the incumbent bank.

[3] We abstract from a direct production cost for portable data to isolate the strategic cost central to the model: under borrower ownership, producing portable data also strengthens the entrant. A standard convex production cost would change production levels but would preserve this appropriability wedge under conventional regularity conditions.

regime does the fintech observe the contents of the bank's non-portable data.

Signal structure. Each lender processes its available data into screening information. In particular, the bank uses its portable and non-portable data to generate a private signal $s_B \in \mathcal{S} = \{g, b\}$ about X. We assume a symmetric signal structure. Conditional on X and the data stocks, the bank's and fintech's signal errors are independent. This assumption captures technology-specific processing noise and creates an information-diversification benefit when both lenders screen the same borrower:

$$\Pr(s_B = g \mid X = R) = \Pr(s_B = b \mid X = 0) = \phi_B(I, K) \in \left(\frac{1}{2}, 1\right). \tag{1}$$

Here, $\phi_B(I, K)$ is differentiable and satisfies

$$\frac{\partial \phi_B(I,K)}{\partial I} > 0, \qquad \frac{\partial \phi_B(I,K)}{\partial K} > 0. \tag{2}$$

Thus, both portable and non-portable data improve the precision of the bank's signal. We do not impose a general restriction here on whether the two data inputs are complements or substitutes in the bank's signal technology. We further assume

$$\phi_B(0, K) > \frac{(R-1)\theta}{(R-1)\theta + (1-\theta)} \quad \text{for all } K \in [\underline{K}, \overline{K}], \qquad \phi_B(\overline{M}, \overline{K}) = \overline{\phi}^{\max} < 1, \tag{3}$$

so that even without portable data, lending after a bad bank signal has negative expected value even at the maximum feasible interest rate. The second condition ensures that even the largest admissible stocks of portable and non-portable data do not reveal X perfectly.

Under lender ownership, the fintech has access to neither portable nor non-portable data. It therefore has no private information about X beyond the prior θ. For notational convenience, we represent this case as the fintech receiving an uninformative signal with precision $1/2$. Under borrower ownership, conditional on entry, the fintech observes the portable data and generates a private signal $s_F \in \mathcal{S}$. Its signal structure is also symmetric:

$$\Pr(s_F = g \mid X = R) = \Pr(s_F = b \mid X = 0) = \phi_F(I; e_F) \in \left[\frac{1}{2}, 1\right]. \tag{4}$$

The parameter e_F indexes the fintech's analytical efficiency: for a given stock of portable data, it governs the precision of the screening information the fintech generates. We suppress the argument e_F until the comparative-statics analysis in Section 5. For a fixed e_F, we assume that $\phi_F(I)$ is differentiable and satisfies

$$\phi_F(0) = \frac{1}{2}, \qquad \phi_F(\overline{M}) \in \left(\phi_B(\overline{M}, \overline{K}), 1\right), \qquad \frac{\partial \phi_F(I)}{\partial I} > 0. \tag{5}$$

Thus, the fintech's screening accuracy improves with the amount of portable data. Importantly, we do not assume that the fintech is better informed at every level of portable-data production. Rather, under borrower ownership its analytical advantage becomes strong enough at high levels of I that, even when the bank has the largest admissible non-portable data endowment, equation (5) implies that $\phi_F(\overline{M}) > \phi_B(\overline{M}, K)$ for all $K \in [\underline{K}, \overline{K}]$. Hence, for sufficiently high levels of portable data, the fintech's signal becomes more precise than the bank's. This endpoint condition allows the fintech to have a sufficiently strong technological advantage without requiring it to dominate the bank for smaller portable data stocks.

Lending competition. At $t = 2$, after observing the bank's portable data production at $t = 1$, the fintech decides whether to enter the lending market. To emphasize the strategic role of data production, we use a vanishing-entry-cost convention. Specifically, the fintech incurs a positive entry cost c_F, and we study the limit as $c_F \downarrow 0$. Let $\Psi_F^E(I; K)$ denote its gross ex-ante payoff from entry, before the entry cost. In the limit, the fintech enters if $\Psi_F^E(I; K) > 0$ and stays out if $\Psi_F^E(I; K) \leq 0$. Thus, a zero gross payoff is sufficient for entry deterrence.

If the fintech stays out, the bank is the monopoly lender. If the fintech enters, then after observing their private signals at $t = 3$, the bank and the fintech simultaneously choose loan offers. Let r_i denote lender i's interest rate offer, where $i \in \{B, F\}$. The action space is $\mathcal{R} \equiv [0, R-1] \cup \{\infty\}$, where $r_i = \infty$ means that lender i chooses not to lend. The upper bound $R - 1$ reflects the borrower's repayment capacity, and negative rates are never optimal.

Because the lenders' signals are correlated through the common payoff state, each lender faces a winner's curse: conditional on its own signal, winning the borrower may

indicate that the rival received less favorable information and therefore bid less aggressively (Milgrom and Weber 1982; Engelbrecht-Wiggans et al. 1983; Broecker 1990; He et al. 2023; Blickle et al. 2025; Goldstein et al. 2025).

Payoffs. Let $W_i(r_i, r_j)$ be an indicator function with $W_i(r_i, r_j) = 1$ indicating that the borrower selects lender i, including the tie-breaking rule specified above. Because offers are simultaneous, a lender does not observe its rival's offer before bidding. Instead, it accounts for the information conveyed by the event that its offer wins. For a lender with signal s_i, let

$$q_i(r_i \mid s_i, I, K) \equiv \Pr\big(W_i(r_i, r_j) = 1 \mid s_i, I, K\big)$$

denote its probability of winning, and let

$$\alpha_i(r_i, s_i; I, K) \equiv \Pr\big(X = R \mid s_i, W_i(r_i, r_j) = 1, I, K\big)$$

denote its posterior probability of success conditional on winning. Conditional on fintech entry, lender i's interim expected payoff from a finite offer r_i is

$$\begin{aligned} \Pi_i^E(r_i \mid s_i, I, K) &= \mathbb{E}\big[W_i(r_i, r_j)\,(\mathbf{1}\{X = R\}(1 + r_i) - 1) \mid s_i, I, K\big] \\ &= q_i(r_i \mid s_i, I, K)\,[\alpha_i(r_i, s_i; I, K)(1 + r_i) - 1], \qquad i \in \{B, F\}, \end{aligned} \tag{6}$$

where the payoff is zero when losing the competition; choosing $r_i = \infty$ also yields zero. If the fintech chooses to stay out, the bank's payoff is determined by monopoly lending. Let $\Pi_B^{NE}(I, K)$ denote the bank's expected payoff when the fintech does not enter.

For a fixed ownership regime and non-portable data endowment, the bank anticipates the entry decision at $t = 2$ and the ensuing lending outcome at $t = 3$ when choosing portable-data production at $t = 1$. Its ex-ante payoff is

$$\Psi_B(I; K) = \begin{cases} \Pi_B^{NE}(I, K), & \text{if the fintech stays out,} \\ \mathbb{E}\big[\Pi_B^E \mid I, K\big], & \text{if the fintech enters.} \end{cases} \tag{7}$$

Strategies and equilibrium. The model timeline is summarized in Figure 1.

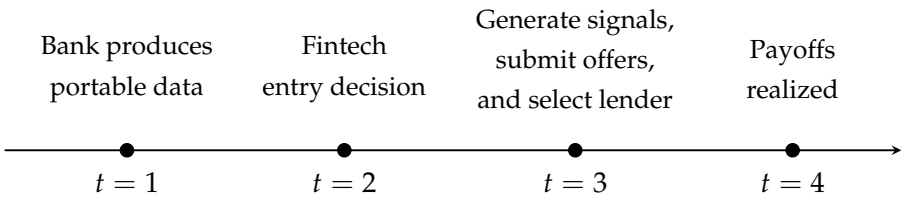


Figure 1: Timeline of strategies and outcomes

Because the borrower's choice between loan offers is straightforward, we focus on lenders' strategies. At $t = 1$, the bank chooses $I \in [0, \overline{M}]$. At $t = 2$, the fintech's entry strategy is a mapping from the bank's portable data choice at $t = 1$ to an entry decision, $\delta_F : [0, \overline{M}] \to \{E, NE\}$, where K and the ownership regime are held fixed.

At $t = 3$, if the fintech stays out, the bank's monopoly lending strategy is a mapping $\beta_B^{NE} : [0, \overline{M}] \times \mathcal{S} \to \Delta(\mathcal{R})$. If the fintech enters, lender i's lending strategy is a mapping $\beta_i^E : [0, \overline{M}] \times \mathcal{S} \to \Delta(\mathcal{R})$ for $i \in \{B, F\}$, where $\Delta(\mathcal{R})$ denotes the set of probability distributions over loan offers. Pure offers are included as degenerate distributions. We focus on monotone perfect Bayesian equilibria, in which the distribution of offers following a good signal is weakly more aggressive than that following a bad signal.

Definition 1. *A* monotone perfect Bayesian equilibrium *consists of a bank data-production choice I^*, a fintech entry strategy δ_F^*, bank lending strategies $\{\beta_B^{NE*}, \beta_B^{E*}\}$, a fintech lending strategy β_F^{E*}, and a belief system (α_B, α_F) such that:*

1. *I^* maximizes the bank's ex-ante payoff in equation (7), given the continuation strategies;*
2. *for every $I \in [0, \overline{M}]$, $\delta_F^*(I) = E$ if $\Psi_F^E(I; K) > 0$ and $\delta_F^*(I) = NE$ if $\Psi_F^E(I; K) \leq 0$, under the vanishing-entry-cost convention;*
3. *if the fintech stays out, the bank's monopoly strategy β_B^{NE*} is sequentially rational;*
4. *if the fintech enters, then for each lender $i \in \{B, F\}$, every offer in the support of β_i^{E*} maximizes equation (6) given beliefs and the rival lender's equilibrium strategy;*
5. *beliefs are formed by Bayes' rule wherever possible; and*

6. *lending strategies are monotone in signals. Specifically, if $G_{i,s}(r \mid I)$ is the equilibrium cumulative distribution of lender i's offer following signal s, then, for every relevant continuation game,*

$$G_{i,g}(r \mid I) \geq G_{i,b}(r \mid I)$$

for all $I \in [0, \overline{M}]$ and every finite $r \in \mathcal{R}$.

3 Lending Market Competition Equilibrium

We solve the model by backward induction. In this section, conditional on fintech entry, we characterize the lending-market competition equilibrium for any given pair of private signal precisions (ϕ_B, ϕ_F). This characterization is useful not only because it is a key input into the bank's optimal portable-data production problem, but also because it provides a tractable analysis of lending competition as a first-price common-value auction for any given pair of information precisions. More broadly, the framework may be useful in other settings in which agents endogenously choose private information precision before competing in a lending market.

Fix a pair of private signal precisions (ϕ_B, ϕ_F). Because our later analysis implies that the bank never chooses portable data production such that $\phi_F > \phi_B$, we focus on the case $\phi_B \geq \phi_F$. Define the signal likelihood ratios and prior odds by

$$\lambda_B = \frac{\phi_B}{1-\phi_B}, \qquad \lambda_F = \frac{\phi_F}{1-\phi_F}, \qquad \lambda_\theta = \frac{\theta}{1-\theta}. \tag{8}$$

For lender $i \in \{B, F\}$, λ_i is the likelihood ratio associated with a good signal, $\Pr(s_i = g \mid X = R)/\Pr(s_i = g \mid X = 0)$; a bad signal has likelihood ratio λ_i^{-1}. The term λ_θ is the prior odds of an H-borrower.

For a signal profile (s_B, s_F), write $\pi^{s_B s_F} \equiv \Pr(X = R \mid s_B, s_F)$ for the posterior probability that the borrower is an H-borrower. Bayes' rule gives

$$\pi^{gg} = \frac{\lambda_B \lambda_F \lambda_\theta}{1 + \lambda_B \lambda_F \lambda_\theta}, \quad \pi^{gb} = \frac{\lambda_B \lambda_F^{-1} \lambda_\theta}{1 + \lambda_B \lambda_F^{-1} \lambda_\theta}, \quad \pi^{bg} = \frac{\lambda_B^{-1} \lambda_F \lambda_\theta}{1 + \lambda_B^{-1} \lambda_F \lambda_\theta}, \quad \pi^{bb} = \frac{\lambda_B^{-1} \lambda_F^{-1} \lambda_\theta}{1 + \lambda_B^{-1} \lambda_F^{-1} \lambda_\theta}.$$

Online Appendix IA.2 collects the posterior formulas and the derivation of the mixed-

strategy equilibrium. The central force is the winner's curse: conditional on winning the borrower, a lender infers that the rival likely observed less favorable information and therefore bid less aggressively. The severity of this winner's curse depends on both lenders' signal precisions, (ϕ_B, ϕ_F), generating the sharp three-region partition of the bank-advantage portion of the precision space developed next.

3.1 A three-region partition of the bank-advantage precision space

For a fixed R, the bank-advantage portion of the precision space, where $\phi_B \geq \phi_F$, is partitioned into the blind bid region, the accommodation region, and the deterrence region. Two indices determine this partition. The first asks whether lending remains profitable even after the worst signal profile, (b, b). The corresponding payoff is

$$\Delta_s \equiv \pi^{bb} R - 1 = \frac{\lambda_\theta (R-1) - \lambda_B \lambda_F}{\lambda_\theta + \lambda_B \lambda_F}. \tag{9}$$

Thus, $\Delta_s > 0$ supports bidding even after both lenders receive bad signals, while $\Delta_s = 0$ defines the blind bid boundary.

The second index governs entry by the less-informed lender. Let

$$\bar{r} \equiv \min\{R, 1 + \lambda_B \lambda_F \lambda_\theta^{-1}\}.$$

The associated entry-support index is

$$\Delta_l \equiv \lambda_\theta (\bar{r} - 1)(1 - \phi_F) + \lambda_B^{-1}(1 - \phi_F) - \lambda_F^{-1}. \tag{10}$$

On the nonblind-bidding branch, where $\bar{r} = R$, this index has the same sign as the less-informed lender's expected payoff after a good signal. $\Delta_l > 0$ supports accommodation and active competition, whereas $\Delta_l \leq 0$ drives the less-informed lender's equilibrium payoff to zero. Hence, with the arbitrarily small positive entry cost, $\Delta_l = 0$ is the entry-deterrence boundary at which that lender's post-good-signal payoff is driven to zero. On the blind-bidding branch, where $\bar{r} = 1 + \lambda_B \lambda_F \lambda_\theta^{-1}$, we always have $\Delta_l > 0$: the less-informed lender earns a positive payoff after a good signal, and entry is supported. Hence, the entry-deterrence boundary lies entirely on the nonblind-bidding branch. To-

gether, Δ_s and Δ_l map profitability and informational asymmetry into market structure.

Lemma 1 formally characterizes the three regions and provides conditions under which all three regions exist and have non-empty interiors.

Lemma 1. *For a fixed R, the bank-advantage portion of the (ϕ_B, ϕ_F)-space, defined by $\phi_B \geq \phi_F$, is partitioned into three non-overlapping and exhaustive regions:*

$$\textit{deterrence region (denoted by } \mathcal{D}) \quad : \quad \Delta_l \leq 0, \tag{11}$$

$$\textit{accommodation region (denoted by } \mathcal{Q}) \quad : \quad \Delta_l > 0 \quad \textit{and} \quad \Delta_s \leq 0, \tag{12}$$

$$\textit{blind bid region(denoted by } \mathcal{B}) \quad : \quad \Delta_l > 0 \quad \textit{and} \quad \Delta_s > 0. \tag{13}$$

Moreover, along the line $\phi_F = 1/2$, each of the three regions has positive measure in ϕ_B if and only if

$$\frac{1}{\theta} < R < \frac{2-\theta}{\theta}. \tag{14}$$

Lemma 1 shows that lending outcomes depend jointly on project profitability and the degree of information asymmetry. Condition $R > 1/\theta$ ensures that, along the line $\phi_F = 1/2$, the economy does not lie everywhere in the deterrence region. Condition $R < (2-\theta)/\theta$ ensures that, along the same line, the deterrence region is also nonempty. Hence, when condition (14) holds, the line $\phi_F = 1/2$ passes through the blind bid region, the accommodation region, and the deterrence region as ϕ_B increases. This intermediate range of R is the most relevant one for the analysis below, because the benchmark with no portable data starts from $\phi_F = 1/2$.

Moreover, viewing the two boundaries $\Delta_s = 0$ and $\Delta_l = 0$ as mappings from ϕ_B to ϕ_F, we can show that ϕ_F decreases in ϕ_B along $\Delta_s = 0$ but increases in ϕ_B along $\Delta_l = 0$. It then follows from condition (14) that all three regions have non-empty interiors within the bank-advantage portion of the (ϕ_B, ϕ_F)-space.

Figure 2 illustrates the three regions characterized in Lemma 1.

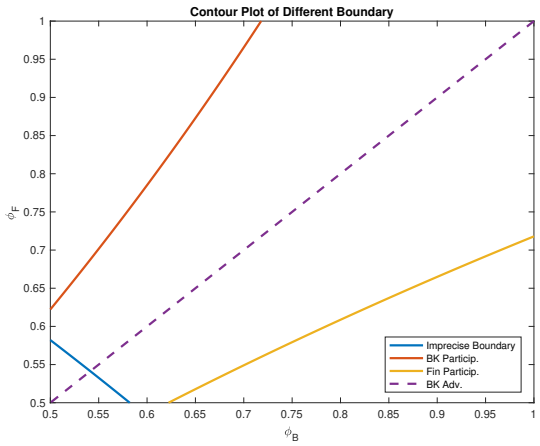


Figure 2: Partition of the bank-advantage precision space. The dashed 45° line separates the bank-advantage and fintech-advantage portions. On and below this line, the solid boundaries $\Delta_s = 0$ and $\Delta_l = 0$ separate the blind bid, accommodation, and deterrence regions.

The dashed 45° line separates the bank-advantage and fintech-advantage areas. The two solid boundaries partition the bank-advantage area according to whether lenders bid after bad signals, whether both remain active after good signals, or whether the less-informed lender is driven to zero expected payoff after a good signal.

The economic intuition for the three regions is straightforward. In the blind bid region, the project return is sufficiently high that even a lender observing a bad signal is willing to bid. Signals therefore have limited disciplinary force on bidding, and both lenders remain active even after unfavorable information.

In the accommodation region, a bad signal is strong enough to eliminate bidding, so both lenders bid only after receiving a good signal. However, the precision gap is still not large enough to drive the less-informed lender's expected payoff after a good signal to zero. Both lenders therefore remain active after good signals and compete head-to-head through mixed strategies.

In the deterrence region, information asymmetry is sufficiently large that the less-informed lender's expected payoff after a good signal is zero in equilibrium. Conditional on entry, it bids after a good signal with probability in $(0, 1]$—strictly below one in the interior of the region—while the more-informed lender always bids after a good signal.

3.2 Fintech entry and continuation payoffs

Although Lemma 1 shows that all three regions can arise in the (ϕ_B, ϕ_F)-space, the maintained assumptions rule out the blind bid region for every feasible level of portable data production. At $I = 0$, equation (3) implies $\Delta_s \leq 0$. As I increases, both likelihood ratios λ_B and λ_F rise, so the condition $\Delta_s > 0$, which requires $\lambda_B \lambda_F < \lambda_\theta(R-1)$, cannot become satisfied. Hence, $\Delta_s \leq 0$ for every $I \in [0, \overline{M}]$. On the bank-advantage side, we can therefore restrict attention to the accommodation and deterrence regions. The following proposition maps each precision pair in these two regions into bidding and entry outcomes.

Proposition 1. *Fix (ϕ_B, ϕ_F) with $\phi_B \geq \phi_F$.*

1. *If $(\phi_B, \phi_F) \in \mathcal{Q}$, both lenders bid only after receiving a good signal. Their common support is $[l_\mathcal{Q}, R-1]$, where*

$$1 + l_\mathcal{Q} = \frac{R}{1+\lambda_F} + \frac{\lambda_F}{1+\lambda_F}\frac{1}{\pi^{gg}}. \tag{15}$$

The lenders' expected payoffs conditional on receiving a good signal are

$$\overline{\Pi}_B^g = \frac{1}{1+\lambda_B^{-1}\lambda_\theta^{-1}}(1+l_\mathcal{Q}) - 1 > 0, \tag{16}$$

$$\overline{\Pi}_F^g = \frac{1}{1+\lambda_F^{-1}\lambda_\theta^{-1}}(1+l_\mathcal{Q}) - 1 > 0. \tag{17}$$

Hence, the fintech enters; that is, $\delta_F = E$.

2. *If $(\phi_B, \phi_F) \in \mathcal{D}$, then, conditional on entry, the bank always bids after receiving a good signal, whereas the fintech bids with probability in $(0, 1]$. The lower bound of the bidding support is*

$$1 + \tilde{l}_F = 1 + \lambda_F^{-1}\lambda_\theta^{-1}. \tag{18}$$

The lenders' expected payoffs conditional on receiving a good signal are

$$\overline{\Pi}_B^g = \frac{1}{1+\lambda_B^{-1}\lambda_\theta^{-1}}\left(1+\tilde{l}_F\right) - 1 = \frac{1+\lambda_F^{-1}\lambda_\theta^{-1}}{1+\lambda_B^{-1}\lambda_\theta^{-1}} - 1 > 0, \tag{19}$$

$$\overline{\Pi}_F^g = 0. \tag{20}$$

Therefore, with arbitrarily small entry cost, the fintech stays out; that is, $\delta_F = NE$.

In the accommodation region, the less-informed lender retains a positive rent after a good signal and enters. In the deterrence region, the winner's curse drives its gross entry payoff to zero, so an arbitrarily small entry cost deters entry. Online Appendix IA.2 provides the proof and the complete bidding strategies.

Because the bank chooses portable-data production before signals are realized, the relevant continuation value is ex ante rather than conditional on a particular signal. On the bank-advantage portion of the accommodation region, aggregating the payoffs in Proposition 1 across signal realizations yields

$$\Pi^{E}_{B,\mathcal{Q}}(\phi_B, \phi_F) = \theta(R-1)\phi_B(1-\phi_F) - (1-\theta)\phi_F(1-\phi_B). \tag{21}$$

To keep derivative notation compact, we suppress the $\mathcal{Q}$ subscript when denoting derivatives of this payoff function. This expression forms the entry branch of the bank's objective in the production analysis below. For the fintech, aggregation does not alter the entry boundary: its gross ex-ante entry payoff $\Psi^{E}_{F}(I;K)$ has the same sign as $\overline{\Pi}^{g}_{F}$, because it earns zero after a bad signal and receives a good signal with strictly positive probability. Thus, the conditional and unconditional payoff formulations generate the same entry boundary.

As we show below, every equilibrium precision pair satisfies $\phi_B \geq \phi_F$. We therefore focus on the bank-advantage portion of the precision space. Under the maintained no-blind-bid restriction, $\mathcal{Q}$ and $\mathcal{D}$ exhaust the equilibrium-relevant continuation outcomes: the fintech enters in $\mathcal{Q}$ and stays out in $\mathcal{D}$.

Figure 3 plots the bank's continuation payoff under fintech entry and marks the boundary $\Delta_l = 0$. Crossing this boundary changes the continuation outcome from active competition to monopoly lending.

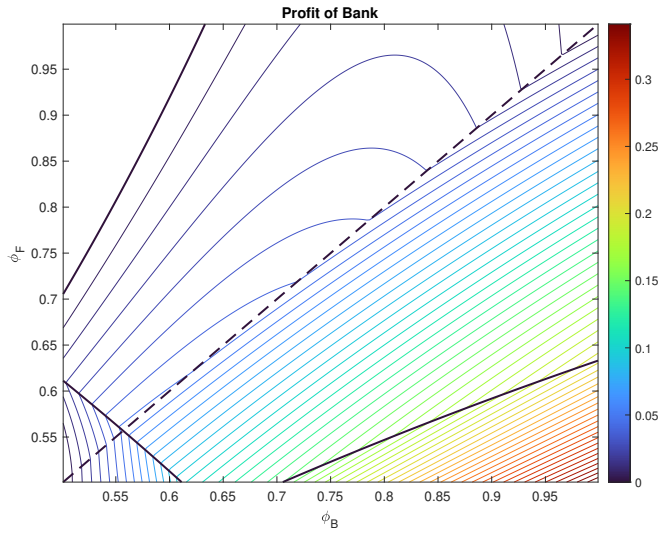


Figure 3: Contour plot of the bank's continuation payoff under fintech entry. The boundary $\Delta_l = 0$ separates the accommodation region, in which the fintech enters, from the deterrence region, in which entry is deterred.

When the fintech stays out, the bank is a monopolist: it does not lend after a bad signal and charges the highest feasible rate, $R - 1$, after a good signal. The switch from accommodation to deterrence therefore generates a discrete upward jump in the bank's equilibrium payoff.

Corollary 1. *For any $(\phi_B, \phi_F) \in \mathcal{D}$ and any $(\phi'_B, \phi'_F) \in \mathcal{Q}$, the bank's equilibrium payoff at (ϕ_B, ϕ_F) is strictly greater than its equilibrium payoff at (ϕ'_B, ϕ'_F).*

Online Appendix IA.1.1 proves the corollary. Figure 4 identifies the two extremal precision pairs underlying the payoff comparison.

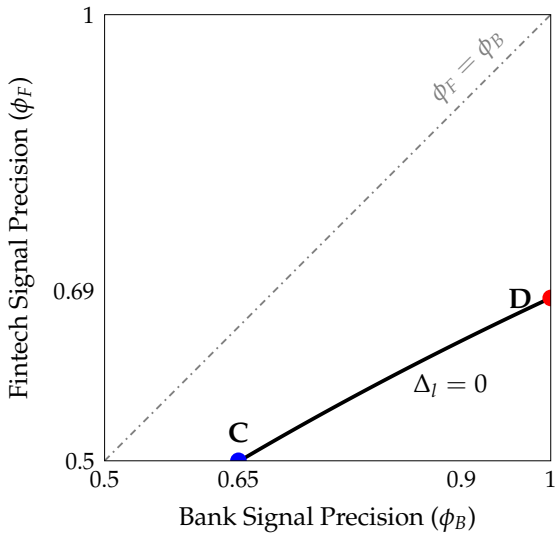


Figure 4: Illustration of Corollary 1. Point C attains the bank's lowest payoff in the deterrence region. Entry points approaching D from the accommodation region attain the supremum of the bank's payoff under entry in the limit. The bank's payoff at C strictly exceeds its payoff at every such entry point.

4 Equilibrium Portable Data Production

Having solved the lending and entry game for any pair of signal precisions, we now turn to the bank's initial portable-data production decision. We first characterize the bank's equilibrium portable data production under borrower ownership. At the end of this section, we compare this outcome with portable data production under lender ownership. This comparison clarifies how policies, such as open banking, that shift data ownership from lenders to borrowers affect equilibrium portable data production.

The bank chooses portable data production before the fintech's entry decision, taking into account that producing more portable data improves its own screening but, under borrower ownership, also raises the fintech's information precision upon entry.

For a given non-portable data endowment K and fintech analytical efficiency, varying portable data production I jointly determines $(\phi_B(I,K), \phi_F(I))$ and traces a one-dimensional path in the (ϕ_B, ϕ_F)-space. We call the set of precision pairs generated in this

way the "feasibility curve":

$$\Gamma \equiv \left\{ (\phi_B(I,K), \phi_F(I)) : I \in \left[0, \overline{M}\right] \right\}. \tag{22}$$

The entry analysis in Section 3.2 implies that the relevant portion of Γ is partitioned into $\Gamma \cap \mathcal{Q}$, where the fintech enters, and $\Gamma \cap \mathcal{D}$, where entry is deterred.

Although we suppress the arguments that determine the shape of Γ whenever there is no confusion, it is useful to emphasize that Γ depends on the bank's non-portable data endowment and the fintech's data analytical efficiency. Section 5 studies how these two primitives affect equilibrium portable data production by changing the shape of Γ.

Without further restrictions on the functional forms of $\phi_B(I,K)$ and $\phi_F(I)$, the feasibility curve Γ cannot be characterized completely. Equations (2) and (5) already imply that the feasibility curve is upward sloping and eventually crosses into the fintech-advantage region. These properties, however, do not determine where the curve begins relative to the entry regions or how its slope compares with the bank's iso-profit curves. We therefore impose the following economically plausible properties.

Assumption 1. *For any given endowment of non-portable data $K \in [\underline{K}, \overline{K}]$, the feasibility curve Γ satisfies the following properties:*

1. ***Monotonicity:*** *Because both lenders' signal precisions strictly increase with portable data production, ϕ_F is strictly increasing in ϕ_B along Γ.*

2. ***Default Entry:*** *Absent portable data production, the precision pair $(\phi_B(0,K), \phi_F(0))$ lies in the accommodation region.*

3. ***Fintech Information Superiority with Sufficient Portable Data:*** *At the maximum level of portable data production $\overline{M}$, the fintech is strictly better informed than the bank even when the bank's endowment of non-portable data is largest; that is,*

$$\phi_F(\overline{M}) > \phi_B(\overline{M}, \overline{K}). \tag{23}$$

4. ***Positive Initial Return to Portable Data:*** *At zero portable-data production, the feasibil-*

ity curve is flatter than the bank's accommodation-region iso-profit curve:

$$\left.\frac{\partial \phi_F(I)/\partial I}{\partial \phi_B(I,K)/\partial I}\right|_{I=0} < -\left.\frac{\Pi^E_{B,\phi_B}}{\Pi^E_{B,\phi_F}}\right|_{(\phi_B(0,K),\phi_F(0))}, \quad \forall K \in [\underline{K}, \overline{K}]. \tag{24}$$

5. ***Relative Convexity:*** *Along* Γ*, the fintech's marginal precision gain accelerates relative to the bank's, so* Γ *is strictly convex:*

$$\frac{\mathrm{d}}{\mathrm{d}I}\left(\frac{\partial \phi_F(I)/\partial I}{\partial \phi_B(I,K)/\partial I}\right) > 0, \quad \forall I \in \left[0, \overline{M}\right]. \tag{25}$$

Assumption 1 imposes a simple geometry on the feasibility curve in addition to previous signal properties assumption as in equations (2) and (5). Specifically we add default entry assumption, positive initial return to portable data assumption, and relative convexity assumption. Default entry assumption ensures that, absent portable data production, the economy starts in the accommodation region. This assumption rules out the less interesting blind bid region, while keeping our analysis non-trivial. The initial-return to portable data assumption says at zero portable data production, the bank's marginal screening gain from portable data, exceeds the marginal competitive loss from improving the fintech's precision. It guarantees that the bank's payoff initially rises with portable-data production so that we focus on interior portable data production. Finally, relative convexity implies that, although portable data improve both lenders' signal precisions, the fintech's marginal precision gain rises relative to the bank's because the fintech has a comparative advantage in processing portable data. As a result, the increase in ϕ_F accelerates relative to the increase in ϕ_B along Γ.

This geometry is useful because it maps the bank's data-production problem into movement along a known path in the (ϕ_B, ϕ_F)-space. As long as the induced precision pair remains in the accommodation region, more portable data have two opposing effects on the bank's payoff. On the one hand, they improve the bank's own screening and hence raise the bank's expected payoff. On the other hand, under borrower ownership, they also raise the fintech's information precision upon entry and intensify lending competition. By contrast, once the induced precision pair enters deterrence region, the fintech does not enter. The bank therefore becomes the monopoly lender. At that point, addi-

tional portable data improve the bank's screening without strengthening a rival lender.

Each portable-data choice selects a precision pair on Γ and thereby determines whether the fintech enters. As established by the production results below, every equilibrium choice satisfies $\phi_B \geq \phi_F$. Focusing on this equilibrium-relevant portion of Γ, the induced pair lies in $\mathcal{Q}$ when the fintech enters and in $\mathcal{D}$ when entry is deterred. Under borrower ownership, the bank therefore chooses $I \in [0, \overline{M}]$ to maximize

$$\Psi_B^{BO}(I;K) = \begin{cases} \Pi_{B,\mathcal{Q}}^{E}\left(\phi_B(I,K), \phi_F(I)\right), & \text{if } (\phi_B(I,K), \phi_F(I)) \in \mathcal{Q}, \\ \Pi_B^{NE}(I,K), & \text{if } (\phi_B(I,K), \phi_F(I)) \in \mathcal{D}, \end{cases} \tag{26}$$

subject to $I \in \left[0, \overline{M}\right]$. Because the objective switches discretely when the feasibility curve crosses the entry-deterrence boundary, the production problem depends on whether Γ reaches $\mathcal{D}$. We analyze the two cases separately.

Equilibrium when $\Gamma \cap \mathcal{D} = \emptyset$. Consider first the case in which the feasibility curve never reaches the deterrence region; that is,

$$\Gamma \cap \mathcal{D} = \emptyset. \tag{27}$$

In this case, any feasible equilibrium choice of portable data must involve fintech entry. The bank therefore chooses I to maximize its continuation payoff under active competition.

The optimal choice balances a screening effect against a competition effect. Taking the first-order derivative of the bank's payoff function with respect to portable data production yields

$$\frac{\mathrm{d}\Pi_{B,\mathcal{Q}}^{E}\left(\phi_B(I,K), \phi_F(I)\right)}{\mathrm{d}I} = \Pi_{B,\phi_B}^{E} \frac{\partial \phi_B(I,K)}{\partial I} + \Pi_{B,\phi_F}^{E} \phi_F'(I). \tag{28}$$

The first term is positive because a more precise bank signal improves screening and raises the expected value of lending. The second term is negative because a more precise fintech signal intensifies competition and reduces the bank's rents. Hence, if the optimum

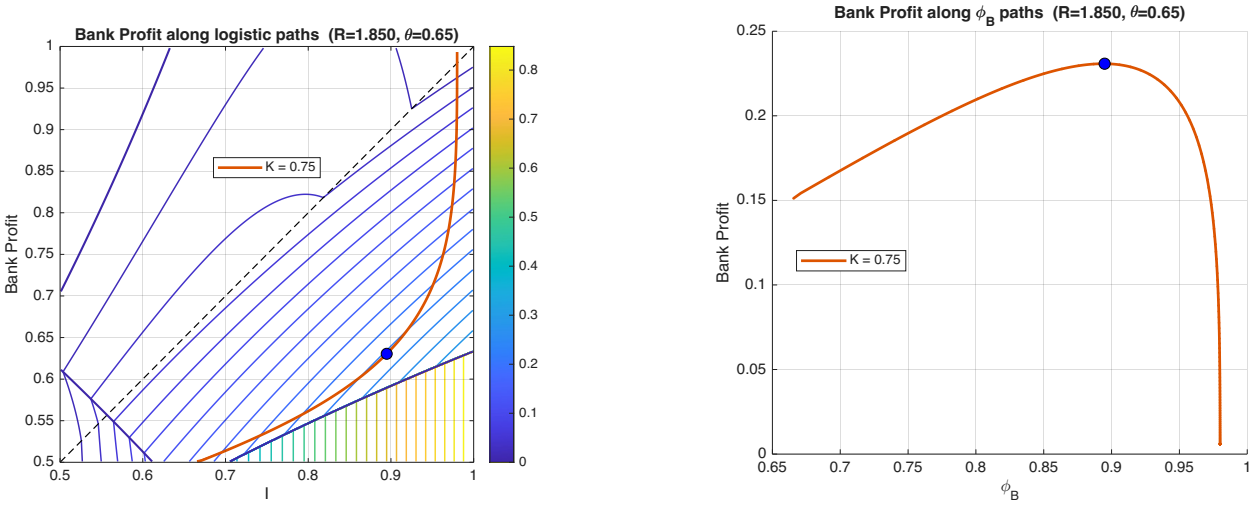
is interior, it is characterized by the first-order condition

$$\frac{\mathrm{d}\Pi^{E}_{B,\mathcal{Q}}\left(\phi_B(I,K),\phi_F(I)\right)}{\mathrm{d}I} = 0. \tag{29}$$

Proposition 2. *Suppose that* $\Gamma \cap \mathcal{D} = \emptyset$. *Then the equilibrium portable data choice under borrower ownership satisfies*

$$I^{BO}_B(K) \in \arg\max_{I\in[0,\overline{M}]} \Pi^{E}_{B,\mathcal{Q}}\left(\phi_B(I,K),\phi_F(I)\right).$$

Furthermore, parts 4 and 5 of Assumption 1 imply that the optimal portable data production is unique, lies in the bank-advantage portion of $\mathcal{Q}$*, and solves equation* (29).



(a) Bank profit along the path induced by portable data production

(b) Bank profit plotted against ϕ_B along the same path

Figure 5: Optimal portable data production when deterrence is infeasible

Proposition 2 delivers the basic tradeoff under borrower ownership. Along the feasibility curve, portable data raise the bank's own signal precision but also strengthen the fintech. The bank's payoff initially rises because the screening gain dominates the competitive loss. As portable data production increases, the slope of the feasibility curve rises while the slope of the bank's iso-profit curve falls. These slopes therefore cross exactly

once, before the path enters the fintech-advantage region, as shown in Online Appendix IA.1.2. The bank consequently chooses a unique interior amount of portable data and accommodates fintech entry. At this optimum, the marginal screening gain is exactly offset by the marginal loss from stronger competition.

Figure 5 illustrates this case for the logistic specification of ϕ_B and ϕ_F. For the displayed parameter values, the feasibility curve induced by portable data production does not reach the deterrence region. Accordingly, the bank chooses an interior level of portable data production, and the fintech enters in equilibrium.

Equilibrium when $\Gamma \cap \mathcal{D} \neq \emptyset$. We next consider the case in which the feasibility curve intersects the deterrence region. Define

$$\widetilde{I}(K) \equiv \sup \left\{ I \in \left[0, \overline{M}\right] : (\phi_B(I,K), \phi_F(I)) \in \mathcal{D} \right\}. \tag{30}$$

Thus, $\widetilde{I}(K)$ is the largest portable-data choice that still keeps the induced precision pair inside the deterrence region. Equivalently, in geometric terms, it is the highest intersection of the feasibility curve $\Gamma(K)$ with the boundary $\Delta_l = 0$.

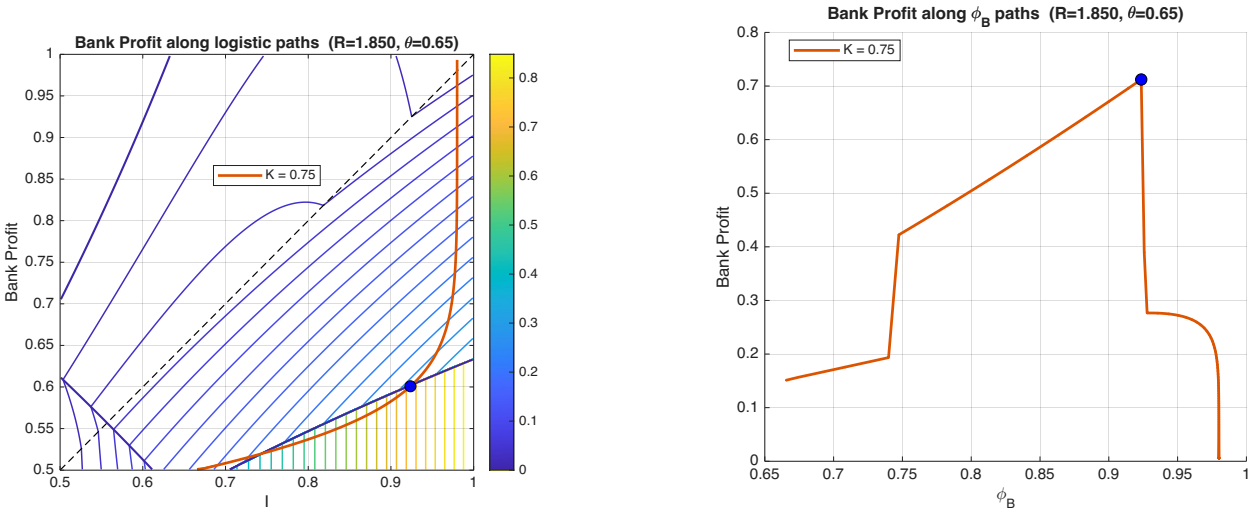
Once the induced precision pair enters the deterrence region, the fintech does not enter. The bank therefore no longer balances screening against competition at an interior point in the competition region. Instead, because additional portable data improve the bank's own screening without inducing fintech entry, the bank chooses the largest amount of portable data consistent with remaining in the deterrence region. Economically, the bank uses data production to strategically deter entry, choosing the highest level of portable data consistent with deterrence. We formalized the result using the following proposition.

Proposition 3. *Suppose that Assumption 1 holds and that the feasibility curve intersects the deterrence region, $\Gamma \cap \mathcal{D} \neq \emptyset$, the equilibrium portable data choice under borrower ownership is*

$$I_B^{BO}(K) = \widetilde{I}(K).$$

Proposition 3, which follows Corollary 1, highlights the discrete nature of the bank's data-production problem. When the feasibility curve reaches the deterrence region, the

bank no longer balances screening against competition at an interior point in the accommodation region. Instead, it switches to deterrence and chooses the maximum amount of portable data consistent with fintech staying out. In this case, portable data production serves both as a screening device and as a means of preventing fintech entry.



(a) Bank profit along the path induced by portable data production

(b) Bank profit plotted against ϕ_B along the same path

Figure 6: Optimal portable data production when the feasibility curve reaches the deterrence region

Figure 6 illustrates the case in which the feasibility curve intersects the deterrence region. The bank then chooses the rightmost point on the path that still lies in the deterrence region. Relative to Figure 5, the role of portable data changes discretely: instead of accommodating entry and balancing the two margin effects inside the accommodation region, the bank uses portable data up to the boundary of the deterrence region so as to keep the fintech out of the lending market.

Comparison with lender ownership. Propositions 2 and 3 characterize the bank's production choice under borrower ownership, depending on whether deterrence is feasible. We now compare these outcomes with the lender-ownership benchmark. Under lender ownership, portable data improve the bank's own signal precision but do not improve the fintech's signal precision. However, borrower ownership introduces an additional nega-

tive externality of portable data production: every extra unit of portable data strengthens the rival lender's precision as well. We formalized the result using the following Corollary 2

Corollary 2. *Let $I_B^{LO}(K)$ denote the equilibrium portable data choice under lender ownership, and let $I_B^{BO}(K)$ denote the equilibrium portable data choice under borrower ownership. Under lender ownership, the bank optimally produces the maximum amount of portable data, $I_B^{LO}(K) = \overline{M}$. By contrast, under borrower ownership, the bank maintains information superiority over the fintech at the optimum; that is,*

$$\phi_B\left(I_B^{BO}(K), K\right) > \phi_F\left(I_B^{BO}(K)\right). \tag{31}$$

Therefore,

$$I_B^{BO}(K) < I_B^{LO}(K). \tag{32}$$

The production ranking in Corollary 2 does not by itself determine whether the uninformed fintech enters under lender ownership. Section 6 states the condition used for the subsequent ownership and welfare comparisons. Corollary 2 summarizes the main ownership comparison. Holding fixed the bank's non-portable data endowment and the fintech's data analytical efficiency, shifting ownership of portable data from the lender to the borrower weakens the bank's incentive to produce portable data. The reason is not that portable data become less useful to the bank or that producing portable data is fiscally costly, but that they become more useful to the bank's rival. This competitive spillover is absent under lender ownership.

5 Comparative Statics of Portable Data Production

Section 4 shows that equilibrium portable data production depends jointly on the bank's non-portable data endowment and the fintech's data analytical efficiency. The key is that these two primitives determine the location and shape of the feasibility curve and, thereby determining whether the bank can use portable data production to deter fintech entry.

In this section, we further analyze how the bank's non-portable data endowment and the fintech's data analytical efficiency affect equilibrium portable data production. The response can be highly non-monotone and, in some cases, exhibit discrete jumps. These

discontinuities arise because small changes in primitives can change whether it is feasible for the bank to deter fintech entry and thereby change the nature of its portable-data choice.

Regime geometry. Before examining the two screening primitives separately, we establish how each affects the feasibility of entry deterrence. On the nonblind-bidding branch, the entry-deterrence boundary $\Delta_I = 0$ can be written as

$$\phi_F = \frac{\phi_B}{1 + [\lambda_\theta(R-1) - 1]\,\phi_B}. \tag{33}$$

The deterrence region lies weakly below this increasing, strictly concave boundary; strict concavity follows from the positive-NPV condition, which implies $\lambda_\theta(R-1) > 1$.

The strict convexity of the feasibility curve and strict concavity of this boundary imply that the deterrence choices form an interval, possibly a singleton at tangency. Moreover, increasing K raises the bank's precision while holding the fintech's precision fixed, making deterrence easier to sustain. Increasing e_F, by contrast, raises the fintech's precision and makes deterrence harder to sustain. The following lemma formalizes these observations.

Lemma 2. *Suppose Assumption 1 holds. On the bank-advantage portion of the precision space:*

1. *For given (K, e_F), the deterrence-inducing choices in $[0, \overline{M}]$ form either the empty set or a closed interval, possibly a singleton at tangency.*

2. *If $K' > K$, every portable-data choice that induces deterrence at (K, e_F) also induces deterrence at (K', e_F).*

3. *If $e'_F > e_F$ and $\phi_F(I; e'_F) \geq \phi_F(I; e_F)$ for every I, every portable-data choice that induces deterrence at (K, e'_F) also induces deterrence at (K, e_F).*

Lemma 2 orders the market-structure regimes in opposite directions across the two primitives. As K increases, the economy can move only from accommodation to deterrence. As e_F increases, it can move only from deterrence to accommodation. Each comparative static can therefore be organized around a single regime threshold.

For the regime-transition results, we focus on parameter ranges in which both entry regimes arise and the transition occurs at an interior portable-data choice. Given the strict convexity of the feasibility curve and the strict concavity of the entry-deterrence boundary, the transition is characterized by a unique tangency. Away from the threshold, the relevant boundary intersection is a crossing.

5.1 Bank Non-portable Data Endowment

We first study how the bank's non-portable data endowment K affects equilibrium portable data production. Richer non-portable data have different effects across entry regimes. When entry must be accommodated, non-portable data crowd out portable data. When deterrence is feasible, richer non-portable data instead allow the bank to produce more portable data while preserving its informational advantage. The equilibrium relationship between the two forms of data therefore depends on market structure.

To sign the accommodation-regime comparative static, we impose the additional condition

$$\frac{\partial^2 \phi_B(I,K)}{\partial I \, \partial K} \leq 0 \tag{34}$$

on the relevant range of I and K. This condition says that the marginal contribution of portable data to the bank's signal precision weakly decreases with its non-portable data endowment. It is used only to establish the crowding-out result under accommodation; the deterrence-regime comparative static and the jump at the regime threshold do not require it.[4]

Lemma 2 implies that these regimes are ordered as K increases. We can therefore define the threshold as the following

$$\widehat{K} \equiv \inf\{K : \Gamma(K) \cap \mathcal{D} \neq \emptyset\}, \tag{35}$$

Below $\widehat{K}$, the bank must accommodate entry. At and above $\widehat{K}$, deterrence becomes feasible. We next explain how the bank's production choice varies within and across these

[4]The proof of the accommodation result requires only $\Pi^E_{B,\phi_B}\phi_{B,IK} + (1-\theta R)\phi_{B,K}\phi'_F < 0$ along the accommodation optimum. Because the second term is strictly negative, equation (34) is sufficient but not necessary and can be replaced by a moderate degree of technological complementarity. We use the simpler primitive condition for transparency.

two regimes.

Accommodation: non-portable data crowd out portable data, $\Gamma(K) \cap \mathcal{D} = \emptyset$. When $K < \widehat{K}$, the feasibility curve does not reach the deterrence region, so the bank chooses the interior production level characterized in Proposition 2. A larger non-portable-data endowment reduces portable-data production through two channels. First, equation (34) makes portable and non-portable data weak substitutes in the bank's screening technology, so a larger K lowers the marginal precision gain from producing portable data. Second, a better-informed bank loses more informational rent when additional portable data strengthen the fintech. Both forces reduce the bank's incentive to produce portable data. Hence,

$$\frac{\mathrm{d}I_B^{BO}(K)}{\mathrm{d}K} < 0, \qquad \textit{when} \quad \Gamma(K) \cap \mathcal{D} = \emptyset \tag{36}$$

Deterrence: non-portable data relax the entry constraint, $\Gamma(K) \cap \mathcal{D} \neq \emptyset$. Once deterrence is feasible, the bank chooses the largest portable-data level consistent with keeping the fintech out, as established in Proposition 3. A larger K raises the bank's precision without directly improving the fintech's precision. It therefore strengthens the bank's informational advantage and relaxes the deterrence constraint. The bank can consequently produce more portable data while still preserving monopoly. Thus, equilibrium portable data production strictly increases with K within the deterrence regime.

The jump at $\widehat{K}$. At $K = \widehat{K}$, the feasibility curve first reaches the deterrence boundary. Immediately below the threshold, the bank accommodates entry and chooses an interior production level. At the threshold, it can instead preserve monopoly by choosing the newly feasible deterrence point. Corollary 1 implies that the bank strictly prefers this deterrence outcome. At the unique interior tangency, however, the newly feasible deterrence point entails less portable-data production than the limiting accommodation optimum. Equilibrium production therefore jumps downward when deterrence first becomes feasible.

The relationship between K and portable-data production is consequently nonmonotonic: production falls with K under accommodation, drops discretely at the regime

threshold, and then rises with K under deterrence. Proposition 4 summarizes this result. Figure 7 illustrates this discontinuity.

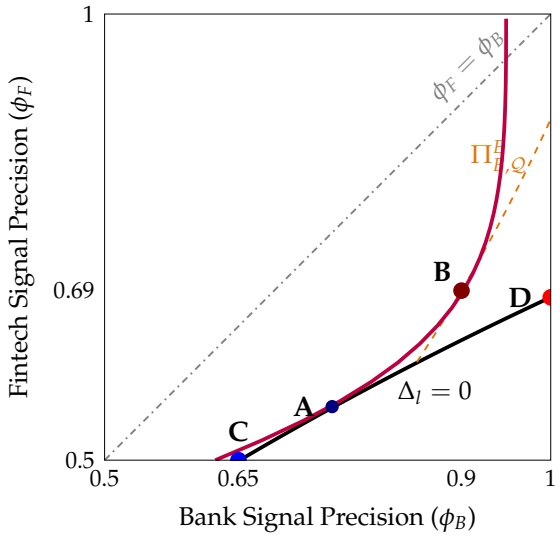


Figure 7: Discrete downward jump in equilibrium portable data production at $\widehat{K}$. Point A is the first-touch point at which the feasibility curve reaches the deterrence region boundary $\Delta_l = 0$. Point B is the interior optimum in the competition region immediately before $\Gamma(K)$ reaches $\mathcal{D}$. Points C and D are, respectively, the lower and limiting upper endpoints of the entry-deterrence boundary. Once deterrence becomes feasible, the bank optimally switches from B to A.

Because the bank's iso-profit curves in the competition region are steeper than the boundary $\Delta_l = 0$, point A must lie to the left of point B on the feasibility curve. Therefore, moving from B to A corresponds to a reduction in portable data production.

To see why this reduction is optimal, note first that the bank is the monopoly lender at both A and C. Because its signal precision is higher at A than at C, the bank's expected payoff at A is strictly greater than that at C. Moreover, Corollary 1 implies that the bank's expected payoff at C is strictly greater than its payoff at B, which lies in the interior of the accommodation region. Therefore, once it becomes feasible to deter fintech entry, the bank prefers point A to point B. As a result, equilibrium portable data production exhibits a discrete downward jump at $\widehat{K}$.

Proposition 4. *Under borrower ownership, the effect of the bank's non-portable data endowment K on equilibrium portable data production depends on whether it is feasible for the bank to deter fintech entry.*

1. *Suppose equation (34) holds. If* $\Gamma(K) \cap \mathcal{D} = \emptyset$*, then equilibrium portable-data production strictly decreases in K:*

$$\frac{\mathrm{d}I_B^{BO}(K)}{\mathrm{d}K} < 0.$$

2. *If* $\Gamma(K) \cap \mathcal{D} \neq \emptyset$*, then equilibrium portable data production is strictly increasing in K within the deterrence regime.*

3. *Equilibrium portable data production is discontinuous at* $\widehat{K}$ *and exhibits a discrete downward jump:*

$$\lim_{K \uparrow \widehat{K}} I_B^{BO}(K) > I_B^{BO}(\widehat{K}) = \lim_{K \downarrow \widehat{K}} I_B^{BO}(K). \tag{37}$$

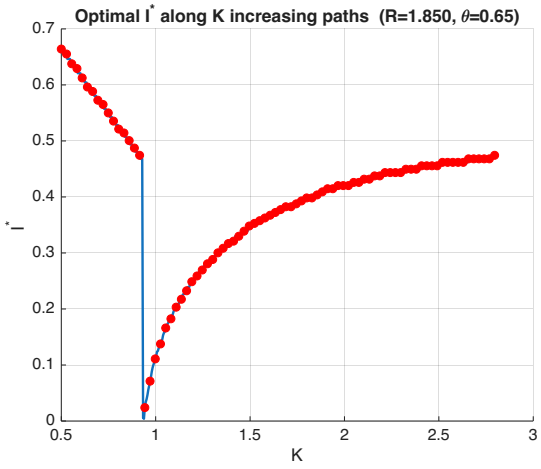
To illustrate the global effect of the bank's non-portable data endowment on equilibrium portable data production, we consider the signal-generation functions

$$\phi_B(I, K) = \frac{1-\delta}{1+\exp\left(-(e_B I + K)\right)}, \tag{38}$$

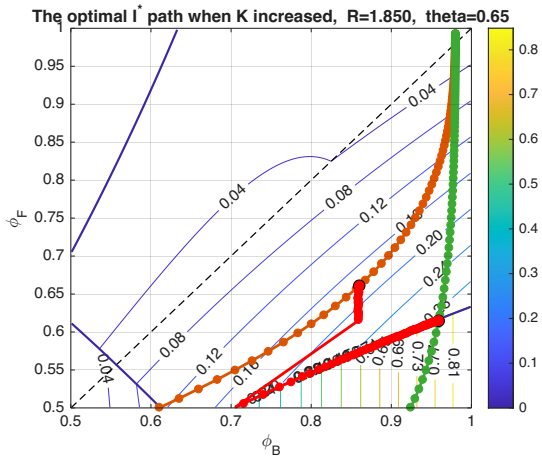
$$\phi_F(I) = \frac{1}{1+\exp\left(-e_F I\right)}. \tag{39}$$

These are the same probabilistic link functions widely used in screening and choice models and in credit scoring (Berg et al. 2020). Here $e_B > 1$ means that one unit of codified portable data contributes more to the bank's information index than one unit of non-portable data. For the parameter values used in the illustration, it is straightforward to verify that these signal-generation functions satisfy equation (34) and Assumption 1.

Figure 8 illustrates Proposition 4. Portable-data production declines with K under accommodation, jumps downward when deterrence first becomes feasible, and subsequently increases within the deterrence regime.



(a) $I^\star$ as K increases



(b) Optimal data production in the (ϕ_B, ϕ_F)-space

Figure 8: Optimal portable data production and non-portable data endowment

5.2 Fintech Data Analytical Efficiency

We next study how the fintech's data analytical efficiency affects equilibrium portable data production. Greater analytical efficiency makes any given amount of portable data more informative to the fintech. It therefore reduces the bank's portable-data production within both entry regimes, although for different reasons. Under deterrence, greater efficiency tightens the entry constraint. Under accommodation, it strengthens the competitive cost of producing portable data. The transition from deterrence to accommodation, however, generates a discrete upward jump in production.

We index the fintech's data analytical efficiency by e_F and impose

$$\frac{\partial \phi_F(I; e_F)}{\partial e_F} > 0, \qquad \frac{\partial^2 \phi_F(I; e_F)}{\partial I \, \partial e_F} > 0 \quad \text{for } I > 0. \tag{40}$$

The first condition means that, for a given stock of portable data, a more efficient fintech generates more precise screening information. The second means that greater efficiency raises the marginal contribution of portable data to the fintech's signal precision. Because the bank's signal technology does not depend on e_F, the second condition also implies that a higher e_F makes the feasibility curve steeper. Thus, greater fintech efficiency shifts the

curve upward and bends it further toward the fintech-advantage region in the (ϕ_B, ϕ_F)-space.

Lemma 2 implies that these regimes are ordered as e_F increases. We can therefore define

$$\widehat{e}_F \equiv \sup \{e_F : \Gamma(e_F) \cap \mathcal{D} \neq \emptyset\}. \tag{41}$$

At and below $\widehat{e}_F$, deterrence is feasible. Above $\widehat{e}_F$, the bank must accommodate fintech entry. We next characterize production within and across these regimes.

Deterrence: fintech efficiency tightens the entry constraint, $\Gamma(e_F) \cap \mathcal{D} \neq \emptyset$. Suppose first that the feasibility curve intersects the deterrence region. By Proposition 3, the bank then chooses the largest amount of portable data consistent with remaining in the deterrence region so that it can deter fintech entry. A higher level of fintech data analytical efficiency makes the portable data more informative for the fintech and therefore reduces the maximum amount of portable data consistent with keeping the fintech out. Hence, as long as it is feasible for the bank to deter fintech entry, equilibrium portable data production decreases with e_F.

The jump at $\widehat{e}_F$. $\widehat{e}_F$ is the highest level of fintech data analytical efficiency for which the feasibility curve still intersects the deterrence region. At $e_F = \widehat{e}_F$, the feasibility curve reaches the boundary $\Delta_l = 0$ for the last time. For $e_F < \widehat{e}_F$ but arbitrarily close to $\widehat{e}_F$, the bank chooses the largest portable-data amount consistent with deterrence, and the induced precision pair lies on the boundary. For $e_F > \widehat{e}_F$, deterrence is no longer feasible, and the bank switches to an interior optimum in the accommodation region.

This switch generates a discrete upward jump in equilibrium portable data production. The reason is that, once deterrence is no longer feasible, the bank no longer has an incentive to restrict portable data production in order to keep the fintech out. Instead, it chooses an interior optimum in the accommodation region, which lies to the right of the limiting deterrence-region point on the feasibility curve. Hence, crossing $\widehat{e}_F$ induces a discrete increase in equilibrium portable data production.

Accommodation: fintech efficiency strengthens the competitive effect of portable data, $\Gamma(e_F) \cap \mathcal{D} = \emptyset$. We next consider values of e_F such that the feasibility curve does not

reach the deterrence region. In this case, the bank chooses an interior level of portable data production characterized by the first-order condition in equation (29). A higher e_F increases the fintech's precision for any given level of portable data production and makes portable data more effective at strengthening the fintech's position in the lending market. As a result, the competition effect of portable data production becomes stronger, reducing the bank's marginal return to portable data production. Hence, once it is not feasible for the bank to deter fintech entry, equilibrium portable data production decreases with the fintech's data analytical efficiency. Proposition 5 summarizes these results.

Proposition 5. *Under borrower ownership, the effect of fintech data analytical efficiency on equilibrium portable data production has three parts. Suppose equation* (40) *holds.*

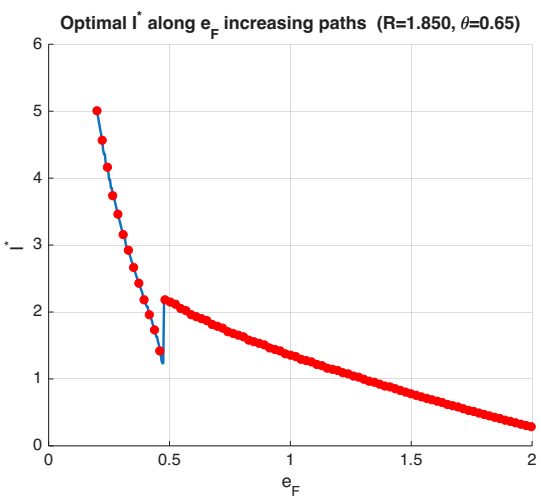
1. *If* $\Gamma(e_F) \cap \mathcal{D} \neq \emptyset$*, then equilibrium portable data production strictly decreases with* e_F *within the deterrence regime.*

2. *Let* $\widehat{e}_F$ *be defined in equation* (41)*. Then equilibrium portable data production is discontinuous at* $\widehat{e}_F$ *and exhibits a discrete upward jump:*

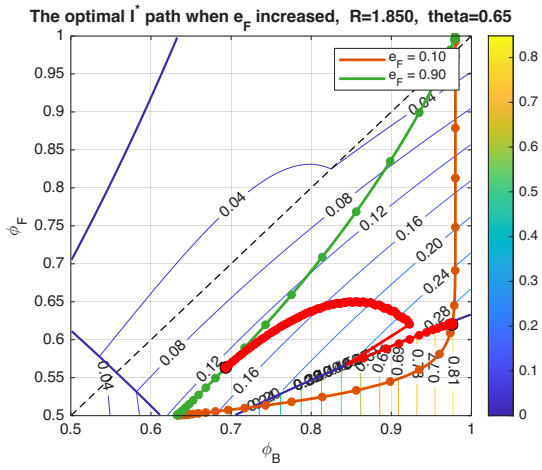
$$\lim_{e_F \to \widehat{e}_F^+} I_B^{BO}(e_F) > I_B^{BO}(\widehat{e}_F). \tag{42}$$

3. *If* $\Gamma(e_F) \cap \mathcal{D} = \emptyset$*, then equilibrium portable data production strictly decreases with* e_F*.*

Logistic illustration. We use the signal-generation functions in equations (38) and (39). Under this specification, a higher e_F directly captures a higher level of fintech data analytical efficiency. For the parameter values used in the illustration, it is straightforward to verify that these functions satisfy equation (40) and the other maintained assumptions. Figure 9 illustrates this comparative static. When fintech efficiency is low enough that deterrence is feasible, equilibrium portable data production declines as e_F rises. Just above $\hat{e}_F$, production jumps up as the bank moves to an interior accommodation optimum. It then declines as e_F rises further. Thus fintech analytical efficiency has a nonmonotone effect on portable data production.



(a) $I^\star$ as e_F increases



(b) Optimal data production in the (ϕ_B, ϕ_F)-space

Figure 9: Optimal Portable Data Production and Fintech Data Analytical Efficiency

6 Credit Availability and Allocative Efficiency

A central policy question is whether shifting data ownership from lenders to borrowers expands credit availability and improves allocative efficiency. In our framework, the answer depends on a fundamental trade-off. On the one hand, borrower ownership broadens lenders' access to borrower data and can induce fintech entry. On the other hand, it weakens the incumbent bank's incentive to produce portable data ex ante.

To evaluate this trade-off, we focus on two outcome measures. The first is credit availability, denoted by $\mathcal{C}$, which is the ex-ante probability that the borrower obtains a loan. The second is allocative efficiency, denoted by $\mathcal{W}$, which we define as

$$\mathcal{W} \equiv \Pr(X = R)\Pr(\text{loan} \mid X = R)(R-1) + \Pr(X = 0)\Pr(\text{loan} \mid X = 0)(-1). \tag{43}$$

Because portable data production is costless, interest payments are transfers between the borrower and lenders, and the fintech's entry cost vanishes, $\mathcal{W}$ coincides with total social surplus in the limit. The only welfare-relevant margin is therefore whether lending decisions are efficient. Funding an H-borrower yields a net surplus of $R-1$, whereas funding an L-borrower destroys one unit of surplus. If no loan is issued, all payoffs are

normalized to zero.

Throughout this section, we hold the bank's non-portable-data endowment K fixed. Under lender ownership, Corollary 2 implies that the bank produces $\overline{M}$. Its equilibrium signal precision is therefore

$$\overline{\phi}^{LO}(K) \equiv \phi_B(\overline{M}, K). \tag{44}$$

This same-K benchmark differs from the global upper bound $\overline{\phi}^{\max} = \phi_B(\overline{M}, \overline{K})$, which evaluates the bank's precision at the largest admissible non-portable-data endowment.

To study an ownership shift from an incumbent-monopoly benchmark, we maintain the lender-ownership deterrence condition

$$\left(\overline{\phi}^{LO}(K), \frac{1}{2}\right) \in \mathcal{D}. \tag{45}$$

Under this condition, lender ownership produces a monopoly bank with precision $\overline{\phi}^{LO}(K)$. The condition remains compatible with fintech entry under borrower ownership because the fintech's precision then increases with portable-data production. All policy comparisons below are conditional on equation (45).

The effect of a data-ownership shift depends on whether it is feasible for the bank to deter fintech entry through its choice of portable data production. If deterrence remains feasible under borrower ownership, shifting ownership does not alter market structure: the bank remains the sole lender in equilibrium, but produces less portable data. If deterrence is not feasible, borrower ownership induces fintech entry. The borrower is then screened using two conditionally independent signals rather than one, increasing the probability that a creditworthy borrower receives funding. We study these two cases in turn and then derive the policy implications.

6.1 When Borrower Ownership Does Not Induce Entry

We begin with the case in which the bank's non-portable data endowment is sufficiently large, or the fintech's data analytical efficiency is sufficiently low, so that it is feasible for the bank to deter fintech entry under borrower ownership. Equivalently, the feasibility curve intersects the deterrence region; that is, $\Gamma \cap \mathcal{D} \neq \emptyset$. Proposition 3 then implies that the bank chooses the largest amount of portable data consistent with deterrence, so that

the fintech does not enter in equilibrium. As a result, shifting data ownership does not alter market structure: the bank remains the sole lender. The ownership shift nevertheless reduces the bank's signal precision.

To quantify the resulting loss in screening precision, let

$$\overline{\phi}^{BO}_{B,\mathcal{D}}(K) \equiv \phi_B\left(I^{BO}_B(K), K\right)$$

denote the bank's equilibrium precision under borrower ownership when deterrence is feasible. Holding K fixed, Corollary 2 implies that

$$I^{BO}_B(K) < I^{LO}_B(K) = \overline{M}.$$

Because $\phi_B(I, K)$ is strictly increasing in portable data production,

$$\overline{\phi}^{BO}_{B,\mathcal{D}}(K) < \phi_B(\overline{M}, K) = \overline{\phi}^{LO}(K).$$

Thus, although the bank remains the sole lender under both ownership regimes, borrower ownership reduces its equilibrium screening precision.

Credit availability. When $\Gamma \cap \mathcal{D} \neq \emptyset$, the bank is the monopoly lender under both ownership regimes, and it lends if and only if it receives a good signal. Hence, credit availability under borrower ownership is

$$\mathcal{C}^{BO}_{\mathcal{D}} = \theta\overline{\phi}^{BO}_{B,\mathcal{D}}(K) + (1-\theta)(1-\overline{\phi}^{BO}_{B,\mathcal{D}}(K)), \tag{46}$$

whereas under lender ownership it is

$$\mathcal{C}^{LO} = \theta\overline{\phi}^{LO}(K) + (1-\theta)(1-\overline{\phi}^{LO}(K)) = 1-\theta+(2\theta-1)\overline{\phi}^{LO}(K). \tag{47}$$

The ownership-induced change in credit availability is therefore

$$\mathcal{C}^{BO}_{\mathcal{D}} - \mathcal{C}^{LO} = (2\theta-1)\left(\overline{\phi}^{BO}_{B,\mathcal{D}}(K) - \overline{\phi}^{LO}(K)\right). \tag{48}$$

Because $\theta > 1/2$ and $\overline{\phi}^{BO}_{B,\mathcal{D}}(K) < \overline{\phi}^{LO}(K)$, borrower ownership reduces credit availability.

Allocative efficiency. Under borrower ownership, allocative efficiency is

$$\mathcal{W}_{\mathcal{D}}^{BO} = \theta\overline{\phi}_{B,\mathcal{D}}^{BO}(K)(R-1) - (1-\theta)(1-\overline{\phi}_{B,\mathcal{D}}^{BO}(K)). \tag{49}$$

Under lender ownership, allocative efficiency is

$$\mathcal{W}^{LO} = \theta\overline{\phi}^{LO}(K)(R-1) - (1-\theta)(1-\overline{\phi}^{LO}(K)). \tag{50}$$

Comparing equations (49) and (50) yields

$$\mathcal{W}_{\mathcal{D}}^{BO} - \mathcal{W}^{LO} = [\theta(R-1) + (1-\theta)]\left(\overline{\phi}_{B,\mathcal{D}}^{BO}(K) - \overline{\phi}^{LO}(K)\right) < 0. \tag{51}$$

Hence, if $\Gamma \cap \mathcal{D} \neq \emptyset$, borrower ownership lowers allocative efficiency.

The economic intuition is straightforward. When the data-ownership shift fails to induce fintech entry, it leaves market structure unchanged while weakening the incumbent bank's screening precision. In that case, borrower ownership cannot generate any competitive benefit and only weakens screening.

6.2 When Borrower Ownership Induces Entry

We next consider the case in which it is not feasible for the bank to deter fintech entry, so that borrower ownership induces fintech entry in equilibrium. Equivalently, the feasibility curve never reaches the deterrence region; that is, $\Gamma \cap \mathcal{D} = \emptyset$. Proposition 2 implies that the equilibrium choice nevertheless lies in $\mathcal{Q}$.

In this case, two lenders are active in equilibrium. This creates a multi-lender benefit: the borrower obtains funding whenever at least one lender receives a favorable signal. At the same time, borrower ownership reduces the amount of portable data produced by the bank relative to lender ownership, so both lenders operate with less precise signals than the monopoly bank would under lender ownership. The net effect on credit availability and allocative efficiency is therefore ambiguous.

Let ϕ_B^{BO} and ϕ_F^{BO} denote, respectively, the equilibrium signal precisions of the bank and the fintech under borrower ownership. Under lender ownership, the monopoly bank attains the same-K precision $\overline{\phi}^{LO}(K)$.

Credit availability. At the borrower-ownership equilibrium, both lenders bid upon receiving favorable signals. The borrower therefore obtains a loan whenever at least one lender observes a good signal. Credit availability under borrower ownership is

$$\begin{aligned} \mathcal{C}_{\mathcal{Q}}^{BO} &= \theta\left[1-(1-\phi_B^{BO})(1-\phi_F^{BO})\right]+(1-\theta)\left[1-\phi_B^{BO}\phi_F^{BO}\right] \\ &= 1-\theta+\theta\phi_B^{BO}+\theta\phi_F^{BO}-\phi_B^{BO}\phi_F^{BO}. \end{aligned} \tag{52}$$

Combining equation (52) with equation (47), borrower ownership increases credit availability if and only if

$$\bar{\phi}^{LO}(K) < \frac{\theta(\phi_B^{BO}+\phi_F^{BO})-\phi_B^{BO}\phi_F^{BO}}{2\theta-1} \equiv \bar{\phi}_{\mathcal{C}}(\phi_B^{BO},\phi_F^{BO}), \tag{53}$$

provided that $\theta > 1/2$. Economically, $\bar{\phi}_{\mathcal{C}}$ is the maximum monopoly-precision benchmark under which the diversification gain from two-lender screening under entry still dominates the precision loss caused by lower endogenous data production.

Condition (53) depends on the endogenous precision pair under borrower ownership. Fintech entry, however, places lower bounds on both precisions. The bank retains access to its non-portable data, so its precision cannot fall below $\phi_B(0,K)$. Moreover, the fintech must be sufficiently well informed to overcome the winner's curse and remain active. This entry condition imposes the fintech precision floor

$$\underline{\phi}_{F,\text{eff}}^{\mathcal{Q}}(K) \equiv \max\left\{\frac{1}{2}, \left[\frac{1}{\phi_B(0,K)}+\frac{\theta(R-1)}{1-\theta}-1\right]^{-1}\right\}.$$

These entry-implied bounds allow us to identify when credit expansion is guaranteed without solving for the exact equilibrium precision pair. The next lemma characterizes when condition (53) is satisfied.

Lemma 3. *Suppose that $\theta > 1/2$ and that (K, e_F) are such that $\Gamma \cap \mathcal{D} = \emptyset$.*

1. *If the entry-implied precision floors satisfy*

$$\left(\theta-\phi_B(0,K)\right)\left(\theta-\underline{\phi}_{F,\text{eff}}^{\mathcal{Q}}(K)\right) \leq (1-\theta)^2,$$

every equilibrium precision pair consistent with entry generates at least as much credit as a perfectly informed monopoly lender. Because $\overline{\phi}^{LO}(K) < 1$*, shifting data ownership to borrowers strictly increases credit availability.*

2. *Otherwise, fintech entry alone does not guarantee credit expansion. Borrower ownership increases credit availability if and only if*

$$\overline{\phi}^{LO}(K) < \bar{\phi}_{\mathcal{C}}\left(\phi_B^{BO}, \phi_F^{BO}\right).$$

Lemma 3 separates fintech entry from credit expansion. When entry imposes sufficiently strong lower bounds on signal precision, the additional independent screen necessarily expands credit. Otherwise, the comparison depends on the equilibrium two-lender screening system and the incumbent's precision under lender ownership.

Allocative efficiency. Under borrower ownership, the probability of correctly funding an H-borrower is $1-(1-\phi_B^{BO})(1-\phi_F^{BO})$, whereas the probability of mistakenly funding an L-borrower is $1-\phi_B^{BO}\phi_F^{BO}$. Allocative efficiency under borrower ownership is therefore

$$\mathcal{W}_{\mathcal{Q}}^{BO} = \theta\left[1-(1-\phi_B^{BO})(1-\phi_F^{BO})\right](R-1) - (1-\theta)\left[1-\phi_B^{BO}\phi_F^{BO}\right]. \tag{54}$$

Comparing equation (54) with equation (50), borrower ownership improves allocative efficiency if and only if the monopoly bank's lender-ownership precision is sufficiently low.

Lemma 4. *Suppose that* (K, e_F) *are such that* $\Gamma \cap \mathcal{D} = \emptyset$*. The shift of data ownership from lenders to borrowers improves allocative efficiency if and only if*

$$\overline{\phi}^{LO}(K) < \frac{\theta(R-1)\left[1-(1-\phi_B^{BO})(1-\phi_F^{BO})\right] + (1-\theta)\phi_B^{BO}\phi_F^{BO}}{\theta(R-1)+(1-\theta)} \equiv \bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO}). \tag{55}$$

Thus, $\bar{\phi}_{\mathcal{W}}$ is the welfare-relevant cutoff. Entry adds a conditionally independent signal but reduces screening precision relative to the lender-ownership monopoly. Borrower ownership improves allocative efficiency only when the diversification benefit dominates this loss, equivalently when $\overline{\phi}^{LO}(K) < \bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO})$.

6.3 Policy Implications

We now characterize when a policymaker who seeks to maximize allocative efficiency should implement policies that shift data ownership from lenders to borrowers.

Proposition 6. *Consider a policymaker whose objective is to maximize allocative efficiency, and suppose the lender-ownership deterrence condition* (45) *holds.*

1. *If* $\Gamma \cap \mathcal{D} \neq \emptyset$*, shifting data ownership from lenders to borrowers is strictly suboptimal:*

$$\mathcal{W}_{\mathcal{D}}^{BO} < \mathcal{W}^{LO}.$$

2. *If* $\Gamma \cap \mathcal{D} = \emptyset$*, shifting data ownership from lenders to borrowers is optimal if and only if*

$$\overline{\phi}^{LO}(K) < \bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO}).$$

Therefore, borrower ownership is socially desirable only when the ownership shift induces fintech entry and the benefit of an additional independent signal dominates the lower signal precision caused by reduced portable data production.

Entry is therefore necessary but not sufficient. Portability reforms are most attractive when they induce entry and the incumbent's lender-ownership precision is sufficiently low for the diversification benefit to dominate the loss in screening precision.

To obtain a complete mapping of the policy's economic effects under competitive entry, it is useful to compare the two thresholds governing credit availability and allocative efficiency. Under $\theta > 1/2$, the credit threshold strictly exceeds the allocative-efficiency threshold:

$$\begin{aligned}\bar{\phi}_{\mathcal{C}}(\phi_B^{BO}, \phi_F^{BO}) - \bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO}) = &\frac{\theta R(1-\theta)}{(2\theta-1)\left[\theta(R-1)+(1-\theta)\right]} \\ &\times \left[\phi_B^{BO}(1-\phi_F^{BO}) + \phi_F^{BO}(1-\phi_B^{BO})\right] > 0.\end{aligned} \tag{56}$$

Thus, whenever borrower ownership improves allocative efficiency, it also expands credit availability. The only possible trade-off is credit expansion with lower allocative efficiency.

Corollary 3. *Suppose $\theta > 1/2$, $\Gamma \cap \mathcal{D} = \emptyset$, and equation (45) holds, so that borrower ownership induces fintech entry whereas lender ownership produces monopoly. Then the policy's impact is characterized by the incumbent bank's same-K lender-ownership precision $\overline{\phi}^{LO}(K)$ as follows:*

1. ***Joint improvement:*** *If*
$$\overline{\phi}^{LO}(K) < \bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO}),$$
then borrower ownership strictly increases both credit availability and allocative efficiency.

2. ***Trade-off region:*** *If*
$$\bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO}) < \overline{\phi}^{LO}(K) < \bar{\phi}_{\mathcal{C}}(\phi_B^{BO}, \phi_F^{BO}),$$
then borrower ownership expands credit availability but lowers allocative efficiency.

3. ***Joint deterioration:*** *If*
$$\overline{\phi}^{LO}(K) > \bar{\phi}_{\mathcal{C}}(\phi_B^{BO}, \phi_F^{BO}),$$
then borrower ownership lowers both credit availability and allocative efficiency.

At the two thresholds, one outcome is unchanged. If $\overline{\phi}^{LO}(K) = \bar{\phi}_{\mathcal{W}}$, borrower ownership increases credit availability while leaving allocative efficiency unchanged. If $\overline{\phi}^{LO}(K) = \bar{\phi}_{\mathcal{C}}$, it lowers allocative efficiency while leaving credit availability unchanged. Moreover, there is no parameter region in which borrower ownership improves allocative efficiency while reducing credit availability.

Corollary 3 provides a complete mapping of the policy's economic effects once borrower ownership succeeds in inducing entry. Joint improvement arises only when the monopoly bank's signal is sufficiently imprecise under lender ownership; that is, when $\overline{\phi}^{LO}(K)$ is sufficiently low. In that case, the benefit of obtaining a second conditionally independent screening signal dominates the loss in signal precision caused by weaker portable data production. By contrast, when $\overline{\phi}^{LO}(K)$ is high, the monopoly bank's signal is already precise under lender ownership, and the loss from reduced portable data production is more likely to dominate the benefit of a second signal.

The corollary also highlights that the most likely tension created by borrower ownership is not between credit contraction and efficiency gains, but rather between greater credit volume and worse credit allocation. In the intermediate region, portability induces

enough entry to expand lending, but not enough screening improvement to offset the decline in signal precision. As a result, more projects are funded, yet the quality of capital allocation declines.

Figure 10 illustrates this partition in the competitive-entry case. For a given benchmark precision $\overline{\phi}^{LO}(K)$, the figure divides the space of precision pairs $(\phi_B^{BO}, \phi_F^{BO})$ into the three outcome zones identified in Corollary 3. As $\overline{\phi}^{LO}(K)$ rises, the lender-ownership benchmark becomes more difficult to outperform, so the joint-improvement region shrinks and the joint-deterioration region expands.

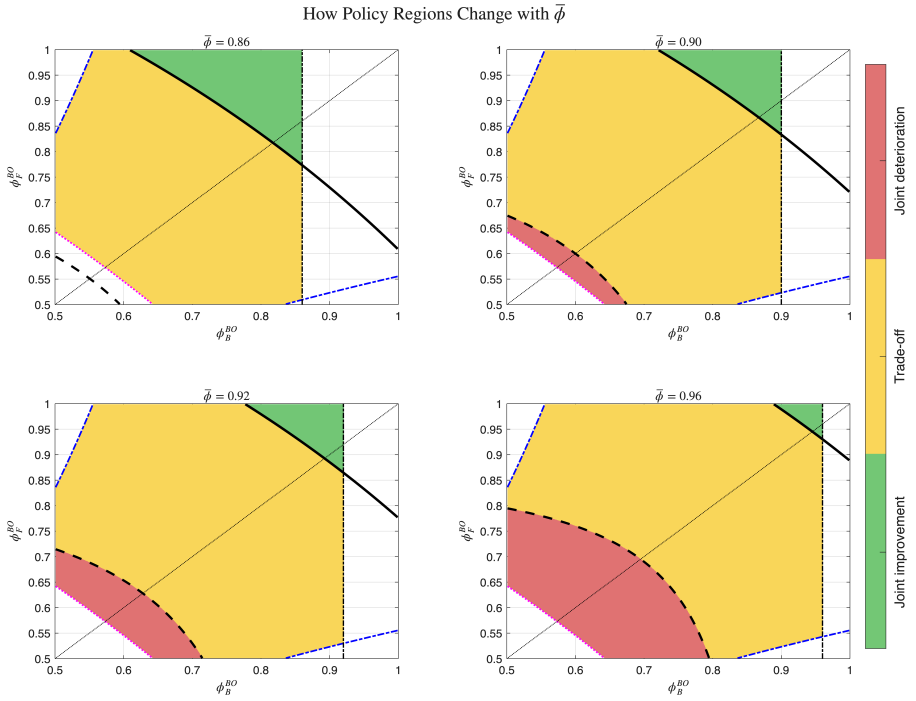


Figure 10: Policy outcome regions in the competitive-entry case. The figure compares the lender-ownership benchmark precision $\overline{\phi}^{LO}(K)$ with the endogenous thresholds $\bar{\phi}_{\mathcal{C}}(\phi_B^{BO}, \phi_F^{BO})$ and $\bar{\phi}_{\mathcal{W}}(\phi_B^{BO}, \phi_F^{BO})$. Because $\bar{\phi}_{\mathcal{C}} > \bar{\phi}_{\mathcal{W}}$ when $\theta > 1/2$, the only trade-off region is the one in which borrower ownership expands credit availability but lowers allocative efficiency. A higher $\overline{\phi}^{LO}(K)$ shrinks the joint-improvement region and expands the joint-deterioration region. Parameters: $R = 1.2$, $\theta = 0.90$.

7 Extensions

This section considers two extensions of the baseline environment. First, we allow the bank to choose the composition of a fixed stock of raw data between portable and non-portable forms. Second, we allow the borrower-ownership regime to attract multiple fintech lenders. Both extensions preserve the central mechanism: portability changes not only the allocation of data across lenders, but also the incumbent's incentive to produce portable data.

7.1 Endogenous Portable Share

The baseline model is most naturally interpreted as applying to future borrowers, for whom portable data have not yet been produced. In that environment, the bank chooses how much portable data to create before the lending market realizes. A related but distinct setting concerns existing borrowers. For these borrowers, the bank may already possess a stock of raw data from past transactions, account histories, and customer interactions. As data-processing and standardization technologies improve, the bank then faces a composition choice rather than a pure scale choice: how much of this existing data should be codified into portable, borrower-level data, and how much should remain in proprietary, non-portable form. The extension below captures this environment by holding fixed the total stock of borrower data and letting the bank choose the portable share.

Formally, the baseline model treats the bank's non-portable data endowment K as fixed and lets the bank choose the amount of portable data I. By contrast, in this extension, the total stock of borrower data is fixed, and the bank chooses how much of it is codified into portable form. Let total data be $M = I + K$ and let

$$I = xM, \qquad K = (1 - x)M, \qquad x \in [0, 1],$$

where x is the portable share.

The asymmetric information index $e_B I + K$ used in the baseline illustration gives this

composition choice economic content. With $e_B > 1$,

$$\phi_B(x; M) = \frac{1-\delta}{1+\exp\{-M[1+(e_B-1)x]\}}, \tag{57}$$

$$\phi_F(x; M) = \frac{1}{1+\exp(-e_F x M)}. \tag{58}$$

At fixed M, converting one unit from non-portable to portable form raises the bank's precision because the bank processes codified data more efficiently, and it also raises the fintech's precision. Thus the change from $I + K$ to $e_B I + K$ preserves the negative cross-partial in the baseline while avoiding a degenerate composition choice in this extension.

Let $\phi_B(x; M)$ and $\phi_F(x; M)$ denote the signal precisions induced by the portable share x. At the all-non-portable allocation, $x = 0$, the fintech receives no portable data and its signal is uninformative, so $\phi_F(0; M) = 1/2$. Under the maintained assumptions below, both lenders' signal precisions increase with the portable share. Thus, for each total data stock M, varying x traces a one-dimensional curve

$$\Gamma_M \equiv \{(\phi_B(x; M), \phi_F(x; M)) : x \in [0, 1]\}.$$

The bank's problem is therefore a geometric problem over a family of feasibility curves indexed by M. Relative to the baseline model, the choice variable is the portable share rather than the portable amount.

Proposition 7. *Suppose that the fixed total amount of borrower data M is large enough that, even with no portable data, the lenders do not bid blindly, i.e. $\left(\phi_B(0; M), \frac{1}{2}\right) \notin \mathcal{B}$. Along the equilibrium-relevant accommodation portion of Γ_M, impose the relative-convexity analogue of Assumption 1: the slope of Γ_M can cross the bank's iso-profit slope at most once, from below. Because both precisions increase with x, Γ_M cannot enter the blind bid region. Then, under borrower ownership:*

1. *If $\Gamma_M \cap \mathcal{D} = \emptyset$, the bank's entry payoff is single-peaked along Γ_M. The optimum is $x_B^{BO}(M) = 0$ if its right derivative at $x = 0$ is nonpositive and $x_B^{BO}(M) = 1$ if its left derivative at $x = 1$ is nonnegative. Otherwise, $x_B^{BO}(M)$ is the unique interior solution to*

$$\frac{\mathrm{d}}{\mathrm{d}x}\mathbb{E}\left[\Pi_B^E \mid x, M\right] = 0.$$

2. *If* $\Gamma_M \cap \mathcal{D} \neq \emptyset$, *the bank chooses*

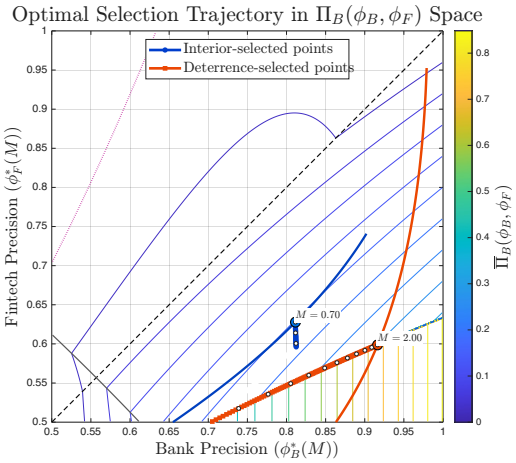
$$x_B^{BO}(M) = \max\{x \in [0,1] : (\phi_B(x;M), \phi_F(x;M)) \in \mathcal{D}\}.$$

Hence, endogenizing the portable share preserves the baseline region-based characterization while allowing both all-non-portable and all-portable corner solutions.

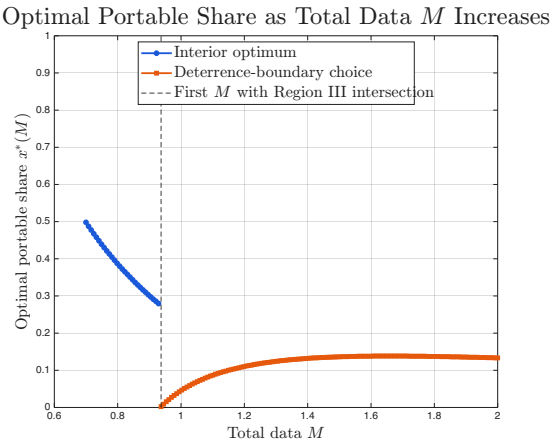
Proposition 7 shows that the main result does not rely on treating non-portable data as an exogenous stock. When the feasible curve does not reach the deterrence region, the bank may choose an all-non-portable allocation, an all-portable allocation, or an interior share. The choice depends on whether the marginal screening gain from portability exceeds the competitive loss at the endpoints. Because these marginal payoffs depend on M, changes in the total data stock can move the optimum between a corner and an interior share. When the feasible curve reaches the deterrence region, the bank instead chooses the largest portable share consistent with keeping the fintech out; this choice may itself be a corner. In particular, the first contact with the deterrence region can occur at $x = 0$, inducing a discrete shift to the all-non-portable allocation. If positive portable shares also deter entry, however, the bank chooses the largest such share because portability continues to improve its own signal.

While the proof of Proposition 7 is relegated to the Online Appendix, we use Figure 11 to illustrate the same logic schematically. As the total stock of borrower data M increases, the induced feasibility curve shifts in the precision space. At the all-non-portable allocation, $x = 0$, the fintech remains uninformed, with $\phi_F(0;M) = 1/2$, while the bank's precision $\phi_B(0;M)$ increases with M. Thus, the left endpoint of Γ_M moves to the right as the bank accumulates more non-portable data about existing borrowers. For positive portable shares, a larger M also means that a given increase in x codifies a larger amount of raw data into portable form. In the displayed illustration, the fintech's precision rises more rapidly along the feasible set, and the curve becomes steeper in the (ϕ_B, ϕ_F) space. Hence, increases in M both strengthen the bank's signal advantage at low portable shares and make portability more consequential for fintech competition at higher portable shares.

In the displayed calibration, at low values of M the feasibility curve does not reach the deterrence region, and the endpoint marginal payoffs have opposite signs, so the



(a) Optimal signal-space trajectory



(b) Optimal portable-data share

Figure 11: Endogenous portable-data share as total data M increases. For each M, varying x traces a feasible curve in (ϕ_B, ϕ_F) space. In the displayed calibration, the bank chooses an interior point when the curve does not reach $\mathcal{D}$ and a deterrence-boundary point once the curve reaches $\mathcal{D}$. Proposition 7 also allows $x = 0$ and $x = 1$.

bank chooses an interior point on Γ_M. Other parameter values can instead produce $x = 0$ or $x = 1$. As total data increase in the illustration, the optimal portable share falls because additional non-portable data strengthen the bank's signal. Once Γ_M reaches the deterrence region, the optimal choice is pinned down by the entry-deterrence boundary.

Figure 12 shows the corresponding data levels implied by the optimal share. For each exogenous total stock M, the bank chooses its split between portable and non-portable forms. The slope change marks the point at which the strategic role of portable data changes from accommodating entry to deterring entry.

7.2 Multiple Fintech Lenders

The baseline model has one potential fintech entrant. We now consider an environment with $N \geq 2$ potential symmetric fintech entrants. Each fintech, upon entering, observes portable data and generates a conditionally independent signal with precision ϕ_F. The bank's precision is ϕ_B.

The fintechs make simultaneous entry decisions and pay an arbitrarily small positive entry cost. We resolve entry indifference in favor of non-entry. When exactly one entrant

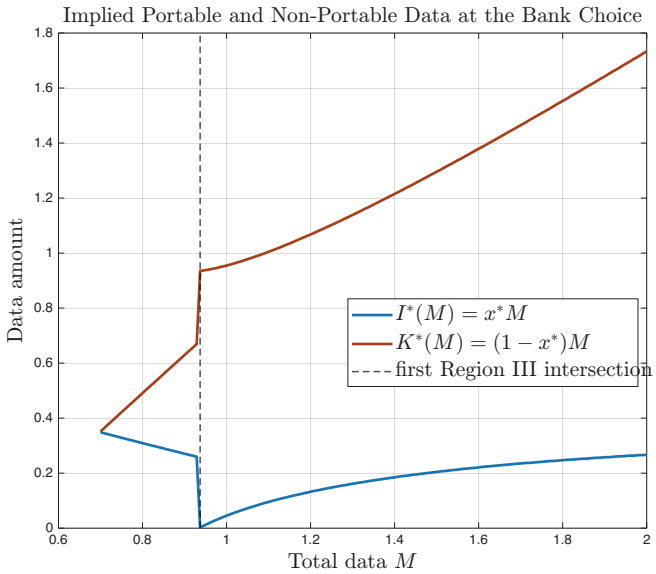


Figure 12: Optimal data composition as total data M increases. The figure decomposes the bank's optimal choice into portable data $I^*(M) = x^*(M)M$ and non-portable data $K^*(M) = (1 - x^*(M))M$. The change in slope reflects the point at which, in the displayed calibration, the optimal portable share switches from an interior solution to the deterrence-boundary choice.

can earn a positive net payoff, there are N symmetric pure-strategy equilibria that differ only in the entrant's identity and therefore generate the same lending and production outcomes.

Consider a candidate outcome with exactly m fintech lenders entering, for any $m \in \{1, \ldots, N\}$. The worst signal profile is that the bank and all m active fintechs receive bad signals. The posterior probability of success after this profile is

$$\pi^{b,b^m} = \frac{1}{1 + \lambda_B \lambda_F^m \lambda_\theta^{-1}}.$$

Define the worst-signal payoff index

$$\Delta_s^{(m)} \equiv \pi^{b,b^m} R - 1 = \frac{\lambda_\theta (R-1) - \lambda_B \lambda_F^m}{\lambda_\theta + \lambda_B \lambda_F^m}. \tag{59}$$

Thus, $\Delta_s^{(m)} = 0$ is the blind-bidding boundary when there are m active fintech lenders.

The effective upper bound of the bidding support is

$$\bar{r}_m \equiv \min\{R, 1 + \lambda_\theta^{-1}\lambda_B\lambda_F^m\}.$$

In addition, the blind-bidding boundaries have a common intercept on the no-portable-data axis as in Figure 2. The equation $\Delta_s^{(m)} = 0$ is equivalent to $\lambda_B\lambda_F^m = \lambda_\theta(R-1)$. Along $\phi_F = 1/2$, we have $\lambda_F = 1$, so the boundary becomes $\lambda_B = \lambda_\theta(R-1)$, or $\phi_B = \lambda_\theta(R-1)/(1+\lambda_\theta(R-1))$, independent of m. Away from this axis, increasing the number of active fintech lenders shifts the blind-bidding boundary to the left. Hence, for a fixed R, as the number of active fintech lenders in the credit market increases, the blind bid region shrinks. This is due to the incremental winner's curse caused by the bad signals of extra new fintech lenders.

Next define the m-entry support index for an individual fintech, conditional on m fintechs entering:

$$\Delta_l^{(m)} \equiv \lambda_\theta(\bar{r}_m - 1)(1-\phi_F)^m + \lambda_B^{-1}(1-\phi_F^m) - \lambda_F^{-1}. \tag{60}$$

Then, if $\Delta_l^{(m)} > 0$, each active fintech earns a positive expected entry payoff, and if $\Delta_l^{(m)} \leq 0$, m active fintech lenders cannot all be sustained. For $m \geq 2$, we call the zero set $\Delta_l^{(m)} = 0$ the m-entry accommodation boundary. Conditional on exactly m fintech lenders entering, this is the boundary at which each active fintech's expected entry payoff is zero. When $m = 1$, the same object is the entry-deterrence boundary from the one-fintech benchmark.

In this extension, the default-entry assumption means that the no-portable-data point $(\phi_B(0,K), \phi_F(0))$ supports exactly one fintech entrant: evaluated at this point, $\Delta_l^{(1)} > 0$ and $\Delta_l^{(2)} \leq 0$.

Figure 13 illustrates the boundary relationships summarized in the next lemma.

Lemma 5. *Suppose $1 > \phi_B > 1/2$, $\phi_B \geq \phi_F \geq 1/2$, and $N \geq 2$. For any fixed (ϕ_B, ϕ_F, R), the set of active fintech counts that can be supported,*

$$\left\{k \in \{1,\ldots,N\} : \Delta_l^{(k)} > 0\right\},$$

is an initial segment of $\{1,\ldots,N\}$. Moreover, for any $m \in \{2,\ldots,N\}$, on the m-entry accommodation boundary $\Delta_l^{(m)} = 0$, a candidate outcome with exactly m active fintech lenders gives each

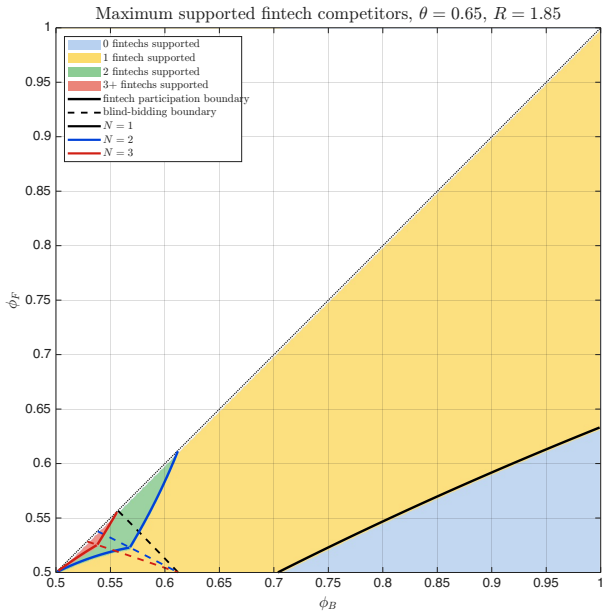


Figure 13: Maximum supported number of fintech lenders. At fixed fintech precision, higher bank precision lowers entrant capacity. The blind-bidding boundaries share a no-portable-data intercept; the accommodation boundaries determine entrant capacity.

active fintech zero expected entry payoff; a candidate outcome with exactly $m - 1$ *active fintech lenders gives each active fintech strictly positive expected entry payoff; and any candidate outcome with* $k > m$ *active fintech lenders gives each active fintech a weakly nonpositive expected entry payoff and therefore cannot be sustained.*

The fixed-precision result does not by itself imply that the maximal entrant count remains one as I changes. We therefore state the path-wide condition used in this extension:

$$\Delta_l^{(2)}\big(\phi_B(I,K), \phi_F(I)\big) \leq 0 \qquad \text{for every } I \in [0, \overline{M}]. \tag{61}$$

On the bank-advantage portion of the path, equation (61) follows from the baseline bad-signal condition in equation (3). In particular, that condition gives $\lambda_B(0,K) > \lambda_\theta(R-1)$; monotonicity then keeps the path to the right of the region in which two entrants can be supported. We impose equation (61) on any off-equilibrium fintech-advantage tail as well. This explicit condition avoids extrapolating the initial-segment result at one precision pair to the entire feasible path.

Proposition 8. *Suppose there are $N \geq 2$ symmetric potential fintechs, entry follows the simultaneous protocol above, and equation (61) holds. Then at most one fintech enters at every portable-data choice. When the one-fintech benchmark accommodates entry, exactly one fintech enters; when it deters entry, none enters. Consequently, the bank's equilibrium portable-data production is identical to that in the one-fintech benchmark.*

Thus, additional potential fintechs change off-equilibrium entry capacity, but under the path-wide condition they do not change the entry outcome relevant for the bank's production choice.

8 Conclusion

This paper shows how data ownership affects lending-market contestability through the endogenous production of portable data. The bank begins with non-portable data and chooses how much portable data to produce before the fintech makes its entry decision. Each lender converts the data available to it into screening information. We model the lending competition as a common-value auction, in which winning the loan is adverse news about the borrower's repayment prospects. The severity of this winner's curse determines whether fintech entry is profitable. Hence, whether the bank can deter entry is therefore governed by the largest bank-favorable information asymmetry attainable along the feasible precision path. A larger non-portable-data endowment strengthens the bank's screening advantage and facilitate entry deterrence, whereas greater fintech analytical efficiency limits that advantage and makes entry deterrence more difficult.

Anticipating this entry boundary changes the bank's data production. Under lender ownership, the bank retains exclusive access to the portable data and produces the maximum amount. Under borrower ownership, producing more portable data also strengthens the fintech's screening. When deterrence is infeasible, the bank accommodates entry and balances its own screening gain against the cost of improving the fintech's information. When deterrence is feasible, it produces the largest amount consistent with preserving monopoly. Consequently, non-portable and portable data are strategic complements under deterrence; under the weak-substitutability condition, they are strategic substitutes under accommodation. Greater fintech analytical efficiency lowers portable-data

production within either regime, while transitions between regimes generate discrete adjustments. Portable-data production can thus respond non-monotonically to changes in the bank's data endowment or the fintech's technology.

Welfare depends on the market structure generated by these production choices. If borrower ownership does not induce entry, the bank remains a monopolist but produces less portable data, reducing screening precision, credit availability, and allocative efficiency. If borrower ownership induces entry, it replaces one relatively precise monopoly signal with two less precise, conditionally independent signals. Welfare improves only when the diversification benefit from the additional signal outweighs the endogenous loss of screening precision. Borrower ownership may therefore expand credit while reducing allocative efficiency.

The paper makes two theoretical contributions. First, it endogenizes data production in the analysis of data rights and shows how data appropriability changes production incentives and, through its effect on relative signal precision and the winner's curse, entry and competition in a common-value lending market. Second, it recasts the bank's data-production choice as the choice of a precision pair along a feasible curve in the signal-precision space, turning the joint production-and-entry problem into a transparent constrained optimization in which entry, deterrence, and the associated production jumps are read off the curve's contact with the regional boundaries. The method extends to endogenous information choices and entry in other common-value auction settings.

The model also provides empirical and policy guidance. The bank's non-portable-data endowment can be proxied by the breadth of its relationship histories, internal account linkages, and proprietary records, while fintech analytical efficiency can be measured by model performance and the compatibility and standardization of available data. The model predicts heterogeneous, and potentially discontinuous, responses of data production, entry, credit, and allocation to portability reforms. For policy, the central question is therefore not simply whether a reform broadens data access, but whether it induces entry after accounting for the incumbent's production response and whether screening diversification outweighs the resulting loss of precision.

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Online Appendix (Not for Publication)

IA.1 Proofs of Lemmas and Propositions

IA.1.1 Proof of Corollary 1

The argument proceeds in three steps. First, in the deterrence region, fintech entry is not profitable, so the bank is a monopolist and its payoff is strictly increasing in ϕ_B. Second, in the accommodation region, the bank's payoff is strictly increasing in its own precision and strictly decreasing in the fintech's precision. Third, the minimum bank payoff in the deterrence region exceeds the supremum of the bank's payoff in the accommodation region. These facts imply Corollary 1.

Step 1: The bank's payoff in the deterrence region

In the deterrence region, the fintech's gross expected payoff conditional on entry is zero. An arbitrarily small positive entry cost therefore keeps it out of the market, and the bank acts as a monopoly lender. Assuming the bank charges the monopoly interest rate $R-1$ upon receiving a good signal (and rejects upon a bad signal), its ex-ante expected payoff is the probability of a good signal multiplied by the expected net return:

$$\begin{aligned}\Pi_B^{NE}(\phi_B) &= P(s_B = g)\left[\Pr(X = R \mid s_B = g)R - 1\right] \\ &= \theta\phi_B(R-1) - (1-\theta)(1-\phi_B). \end{aligned} \tag{62}$$

Taking the first derivative with respect to the bank's signal precision ϕ_B yields:

$$\frac{\partial \Pi_B^{NE}}{\partial \phi_B} = \theta(R-1) + (1-\theta) > 0. \tag{63}$$

Because $\theta \in (0,1)$ and $R > 1$, this derivative is strictly positive. Thus, in the deterrence region, the bank's monopoly payoff is strictly increasing in ϕ_B.

Step 2: The bank's payoff in the accommodation region

In the accommodation region, the fintech enters the market, resulting in a duopoly where lenders compete in a common-value auction. The bank's ex-ante expected pay-

off is given by equation (21). Taking the partial derivatives with respect to both signal precisions gives:

$$\Pi^{E}_{B,\phi_B} = \theta(R-1)(1-\phi_F) + (1-\theta)\phi_F > 0, \tag{64}$$

$$\Pi^{E}_{B,\phi_F} = -\theta(R-1)\phi_B - (1-\theta)(1-\phi_B) < 0. \tag{65}$$

Thus, in the accommodation region, the bank's payoff strictly increases with its own precision ϕ_B (the screening effect) and strictly decreases with the fintech's precision ϕ_F (the competition and adverse selection effects).

Step 3: Dominance of the deterrence region over the accommodation region

Let C denote the endpoint of the boundary $\Delta_l = 0$ at which $\phi_F = 1/2$, and let D denote its limiting endpoint as $\phi_B \uparrow 1$. The supremum of the bank's ex-ante payoff in the accommodation region is approached as the precision pair converges to D and equals $\theta R - 1$. The bank's payoff in the deterrence region is minimized at C, where

$$\Pi^{NE}_{B}(C) = \frac{2(1-\theta)(\theta R - 1)}{3 - 2\theta - \theta R}.$$

For a viable lending market, $\theta R > 1$ and, from the boundary condition, $R < (2-\theta)/\theta$. Hence $(\theta R - 1) > 0$ and $3 - 2\theta - \theta R > 0$, so

$$\Pi^{NE}_{B}(C) - (\theta R - 1) = (\theta R - 1)\left[\frac{\theta R - 1}{3 - 2\theta - \theta R}\right] > 0.$$

Hence, the minimum profit in the deterrence region exceeds the supremum of profit in the accommodation region.

By Steps 1 and 2, any other deterrence-region precision pair gives the bank at least the payoff at C, while every accommodation-region pair gives the bank strictly less than the limiting payoff at D. Therefore every point in $\mathcal{Q}$ gives the bank less than every point in $\mathcal{D}$.

Q.E.D.

IA.1.2 Proof of Proposition 2

Write $A \equiv \theta(R-1)$ and $B \equiv 1-\theta$. The positive-NPV condition implies $A > B$. On the competition portion of the path,

$$\Pi^E_{B,\phi_B} = A(1-\phi_F) + B\phi_F > 0, \qquad \Pi^E_{B,\phi_F} = -A\phi_B - B(1-\phi_B) < 0.$$

Consequently, the slope of the bank's iso-profit curve is

$$S_{\text{iso}}(\phi_B, \phi_F) = -\frac{\Pi^E_{B,\phi_B}}{\Pi^E_{B,\phi_F}} = \frac{A(1-\phi_F) + B\phi_F}{A\phi_B + B(1-\phi_B)} > 0. \tag{66}$$

It strictly decreases as either precision increases. The slope of the feasibility curve is $S_\Gamma = \phi'_F/\phi_{B,I}$ and strictly increases with I by equation (25). Hence $S_\Gamma - S_{\text{iso}}$ is strictly increasing along the bank-advantage portion of Γ.

Equation (24) is exactly $S_\Gamma(0) < S_{\text{iso}}(0)$. Equivalently,

$$\left.\frac{\mathrm{d}\Pi^E_B}{\mathrm{d}I}\right|_{I=0} = \Pi^E_{B,\phi_B}\phi_{B,I}\left(S_{\text{iso}} - S_\Gamma\right) > 0.$$

By equation (23), the path crosses the 45° line. At that crossing its slope exceeds one: strict convexity makes the tangent slope exceed the chord slope from $(\phi_B(0,K), 1/2)$, and that chord has slope greater than one. At a point on the 45° line, equation (66) gives $S_{\text{iso}} < 1$, because $A > B$ and the common precision exceeds $1/2$. Thus the derivative of bank profit is negative by the time the path reaches the 45° line.

Continuity and strict monotonicity of $S_\Gamma - S_{\text{iso}}$ give a unique zero before that crossing. Bank profit rises before this point and falls after it throughout the accommodation region. If the path continues far enough for the bank to become the less informed lender, the role-reversed equilibrium has the same own-precision and rival-precision monotonicities; the bank's payoff continues to fall and is zero if the bank is itself driven out. Therefore no point on the fintech-advantage tail can be optimal. The unique global optimum is interior, lies in the bank-advantage portion of $\mathcal{Q}$, and satisfies equation (29). *Q.E.D.*

IA.1.3 Proof of Proposition 3

Let

$$I_B^{BO}(K) \in \arg\max_{I\in[0,\overline{M}]} \Psi_B^{BO}(I;K),$$

where

$$\Psi_B^{BO}(I;K) = \begin{cases} \Pi_{B,\mathcal{Q}}^{E}\left(\phi_B(I,K),\phi_F(I)\right), & (\phi_B(I,K),\phi_F(I)) \in \mathcal{Q}, \\ \Pi_B^{NE}(I,K), & (\phi_B(I,K),\phi_F(I)) \in \mathcal{D}. \end{cases}$$

Assume $(\phi_B(0,K),\phi_F(0)) \in \mathcal{Q}$ and $\Gamma \cap \mathcal{D} \neq \emptyset$, and define

$$\tilde{I}(K) := \sup\{I \in [0,\overline{M}] : (\phi_B(I,K),\phi_F(I)) \in \mathcal{D}\}.$$

Step 1 (the optimum cannot lie in the accommodation region once the deterrence region is reachable)

By Corollary 1, every precision pair in the deterrence region gives the bank a strictly higher payoff than every pair in the accommodation region. Therefore, once a deterrence-region point is reachable, every accommodation candidate is strictly dominated by a feasible deterrence candidate. Hence, any optimizer must lie in the deterrence region.

Step 2 (optimum within the deterrence region)

In the deterrence region, the fintech is deterred in equilibrium ($\delta_F = NE$), so the bank is the monopoly lender. Equation (62) shows that this payoff is strictly increasing in ϕ_B. By feasibility-curve monotonicity ($\partial\phi_B/\partial I > 0$), $\Pi_B^{NE}(I,K)$ is strictly increasing in I along the deterrence region. Therefore, among all I that keep the precision pair in the deterrence region, the bank chooses the largest feasible one, i.e.

$$I_B^{BO}(K) = \max\{I : (\phi_B(I,K),\phi_F(I)) \in \mathcal{D}\} = \tilde{I}(K).$$

Thus, under borrower ownership, the equilibrium portable-data choice is exactly the rightmost deterrence-region point on Γ.

Q.E.D.

IA.1.4 Proof of Lemma 2

On the bank-advantage, nonblind-bidding portion of the precision space, $\mathcal{D}$ is the set below the boundary in equation (33). That boundary is strictly increasing and concave, whereas Assumption 1 makes the feasibility curve strictly convex. Because $\phi_B(I, K)$ is strictly increasing in I, the feasibility curve can be parameterized by ϕ_B. Its continuous vertical gap from the entry-deterrence boundary is strictly convex, so its weak zero-sublevel set is either empty or a closed interval and is a singleton when the curves only touch. The strictly increasing map from I to $\phi_B(I, K)$ preserves this interval structure, proving part 1.

For a fixed I, increasing K strictly raises $\phi_B(I, K)$ and leaves $\phi_F(I)$ unchanged. Because the entry boundary is increasing, every point that is in $\mathcal{D}$ at K remains in $\mathcal{D}$ at any $K' > K$. This proves part 2. Similarly, increasing e_F weakly raises $\phi_F(I; e_F)$ and leaves ϕ_B unchanged, so any point in $\mathcal{D}$ at $e'_F > e_F$ must also be in $\mathcal{D}$ at e_F. This proves part 3. *Q.E.D.*

IA.1.5 Proof of Proposition 4

When $\Gamma(K) \cap \mathcal{D} = \emptyset$, Proposition 2 gives a unique interior optimum satisfying $V_I(I; K) = 0$, where

$$V_I = \Pi^E_{B,\phi_B}\phi_{B,I} + \Pi^E_{B,\phi_F}\phi'_F.$$

The implicit function theorem gives

$$\frac{\mathrm{d}I^{BO}_B}{\mathrm{d}K} = -\frac{V_{IK}}{V_{II}}, \qquad V_{II} < 0.$$

Since ϕ_F does not depend on K,

$$V_{IK} = \Pi^E_{B,\phi_B\phi_B}\phi_{B,K}\phi_{B,I} + \Pi^E_{B,\phi_B}\phi_{B,IK} + \Pi^E_{B,\phi_B\phi_F}\phi_{B,K}\phi'_F. \tag{67}$$

Equation (21) implies $\Pi^E_{B,\phi_B\phi_B} = 0$, $\Pi^E_{B,\phi_B} > 0$, and $\Pi^E_{B,\phi_B\phi_F} = 1 - \theta R < 0$. Together with $\phi_{B,IK} \leq 0$ from equation (34), $\phi_{B,K} > 0$, and $\phi'_F > 0$, these signs imply $V_{IK} < 0$. Thus $\mathrm{d}I^{BO}_B/\mathrm{d}K < 0$, proving part 1.

When $\Gamma(K) \cap \mathcal{D} \neq \emptyset$, the optimum is the largest portable-data choice that induces

deterrence, $\widetilde{I}(K)$. Consider $K' > K$ such that deterrence is feasible at both endowments. Lemma 2 implies that every choice that induces deterrence at K also induces deterrence at K', so $\widetilde{I}(K') \geq \widetilde{I}(K)$. Moreover, the precision pair induced by $\widetilde{I}(K)$ lies on the entry-deterrence boundary. Because a higher K strictly raises the bank's precision without changing the fintech's precision, the same portable-data choice lies strictly inside the deterrence region at K'. Continuity then implies that some portable-data choice strictly greater than $\widetilde{I}(K)$ also induces deterrence at K'. Therefore, $\widetilde{I}(K') > \widetilde{I}(K)$. This proves part 2.

For part 3, let I_A denote the unique first-contact choice at $K = \widehat{K}$. At this unique interior contact, the feasibility curve is tangent to the entry boundary. Along that boundary,

$$S_{\text{iso}} - \left.\frac{\mathrm{d}\phi_F}{\mathrm{d}\phi_B}\right|_{\Delta_l=0} = \left(\frac{1}{\phi_F} - \frac{1}{\phi_B}\right)\frac{\phi_F}{\phi_B} > 0.$$

Thus, at the contact, the feasibility curve is flatter than the bank's iso-profit curve, so the bank's competition payoff is still increasing in I there. The limiting accommodation optimum as $K \uparrow \widehat{K}$ must therefore lie strictly to the right of I_A. At $K = \widehat{K}$, Corollary 1 makes the bank choose the newly feasible deterrence point I_A. Continuity of the family of feasibility curves and uniqueness of the one-sided optima then imply

$$\lim_{K\uparrow\widehat{K}} I_B^{BO}(K) > I_B^{BO}(\widehat{K}) = I_A = \lim_{K\downarrow\widehat{K}} I_B^{BO}(K),$$

which proves the downward jump. *Q.E.D.*

IA.1.6 Proof of Proposition 5

Suppose first that $\Gamma(e_F) \cap \mathcal{D} \neq \emptyset$. The bank chooses the largest portable-data amount consistent with deterrence, $\widetilde{I}(e_F)$. Consider $e_F' > e_F$ such that deterrence is feasible at both efficiency levels. Lemma 2 implies that every choice that induces deterrence at e_F' also induces deterrence at e_F, so $\widetilde{I}(e_F) \geq \widetilde{I}(e_F')$. At $\widetilde{I}(e_F')$, reducing fintech efficiency from e_F' to e_F strictly lowers the fintech's precision without changing the bank's precision. The induced pair therefore moves from the entry-deterrence boundary into the deterrence region. Continuity then implies that some portable-data choice strictly greater than $\widetilde{I}(e_F')$

also induces deterrence at e_F. Hence, $\widetilde{I}(e_F) > \widetilde{I}(e'_F)$. This proves part 1.

By Lemma 2, $\widehat{e}_F$ is a feasibility threshold: it is the highest efficiency for which the feasible curve reaches $\mathcal{D}$, not a payoff-indifference threshold. Let I_A be the unique last-contact choice at $\widehat{e}_F$. At this unique interior contact, the feasibility curve is flatter than the bank's iso-profit curve because

$$S_{\text{iso}} - \left.\frac{\mathrm{d}\phi_F}{\mathrm{d}\phi_B}\right|_{\Delta_l=0} = \left(\frac{1}{\phi_F} - \frac{1}{\phi_B}\right)\frac{\phi_F}{\phi_B} > 0.$$

Thus the bank's competition payoff is increasing in I at I_A. The unique accommodation optimum on a curve just above $\widehat{e}_F$ lies strictly to the right of the contact point. At $\widehat{e}_F$, Corollary 1 makes the bank choose I_A; immediately above it, deterrence is infeasible. Continuity of the family of curves and of the unique accommodation optimum therefore yields

$$\lim_{e_F \downarrow \widehat{e}_F} I_B^{BO}(e_F) > I_B^{BO}(\widehat{e}_F) = I_A,$$

which proves part 2.

Finally, suppose $\Gamma(e_F) \cap \mathcal{D} = \varnothing$. At the unique interior optimum, $V_I(I; e_F) = 0$ and $V_{II} < 0$. Because the bank's precision does not depend on e_F,

$$V_{Ie_F} = \Pi^E_{B,\phi_B\phi_F}\phi_{F,e_F}\phi_{B,I} + \Pi^E_{B,\phi_F}\phi_{F,Ie_F} + \Pi^E_{B,\phi_F\phi_F}\phi_{F,e_F}\phi_{F,I}. \tag{68}$$

Equation (21) gives $\Pi^E_{B,\phi_B\phi_F} = 1 - \theta R < 0$, $\Pi^E_{B,\phi_F} < 0$, and $\Pi^E_{B,\phi_F\phi_F} = 0$. Equation (40) therefore implies $V_{Ie_F} < 0$. The implicit function theorem gives

$$\frac{\mathrm{d}I_B^{BO}}{\mathrm{d}e_F} = -\frac{V_{Ie_F}}{V_{II}} < 0,$$

proving part 3. *Q.E.D.*

IA.1.7 Proof of Lemma 3

Recall from (53) that credit expands if and only if

$$\overline{\phi}^{LO}(K) < \frac{\theta(\phi_B^{BO} + \phi_F^{BO}) - \phi_B^{BO}\phi_F^{BO}}{2\theta - 1}.$$

A sufficient condition for this inequality to hold for any $\overline{\phi}^{LO}(K) < 1$ is that the right-hand side be weakly greater than 1, that is,

$$\frac{\theta(\phi_B^{BO} + \phi_F^{BO}) - \phi_B^{BO}\phi_F^{BO}}{2\theta - 1} \geq 1.$$

Because $\theta > 1/2$, multiplying through by $2\theta - 1$ and rearranging yields the equivalent condition

$$(\theta - \phi_B^{BO})(\theta - \phi_F^{BO}) \leq (1 - \theta)^2. \tag{69}$$

We next derive lower bounds for both equilibrium precisions under borrower ownership.

First, because the incumbent bank retains the non-portable data endowment K, its signal precision is bounded below by

$$\phi_B^{BO} \geq \phi_B(0, K).$$

Second, because the borrower-ownership equilibrium lies outside the deterrence region, we must have $\Delta_l > 0$. Under the maintained no-blind-bidding restriction, $\bar{r} = R$. Using the definition of Δ_l in (10), this is equivalent to

$$R > 1 + \lambda_\theta^{-1} + (\lambda_F^{-1} - \lambda_B^{-1})\lambda_\theta^{-1}.$$

Substituting $\lambda_B^{-1} = 1/\phi_B^{BO} - 1$, $\lambda_F^{-1} = 1/\phi_F^{BO} - 1$, and $\lambda_\theta^{-1} = (1 - \theta)/\theta$ gives

$$R - 1 > \frac{1 - \theta}{\theta}\left[1 + \left(\frac{1}{\phi_F^{BO}} - 1\right) - \left(\frac{1}{\phi_B^{BO}} - 1\right)\right].$$

Rearranging,

$$\frac{\theta(R-1)}{1-\theta} > \frac{1}{\phi_F^{BO}} - \frac{1}{\phi_B^{BO}} + 1,$$

so

$$\frac{1}{\phi_F^{BO}} < \frac{1}{\phi_B^{BO}} + \frac{\theta(R-1)}{1-\theta} - 1.$$

Since $\phi_B^{BO} \geq \phi_B(0,K)$, it follows that

$$\frac{1}{\phi_F^{BO}} < \frac{1}{\phi_B(0,K)} + \frac{\theta(R-1)}{1-\theta} - 1,$$

and therefore

$$\phi_F^{BO} > \left[\frac{1}{\phi_B(0,K)} + \frac{\theta(R-1)}{1-\theta} - 1\right]^{-1}.$$

Combining this with the primitive feasibility restriction $\phi_F^{BO} \geq 1/2$ yields

$$\phi_F^{BO} \geq \underline{\phi}_{F,\text{eff}}^{\mathcal{Q}}.$$

Thus every feasible borrower-ownership equilibrium pair satisfies

$$\phi_B^{BO} \geq \phi_B(0,K), \qquad \phi_F^{BO} \geq \underline{\phi}_{F,\text{eff}}^{\mathcal{Q}}.$$

On the rectangle $[\phi_B(0,K),1] \times [\underline{\phi}_{F,\text{eff}}^{\mathcal{Q}},1]$, the bilinear expression $(\theta-\phi_B)(\theta-\phi_F)$ reaches its maximum at a corner. The corners with one precision equal to one are weakly below $(1-\theta)^2$, while the corner with both precisions equal to one equals $(1-\theta)^2$. Therefore, if

$$(\theta - \phi_B(0,K))\left(\theta - \underline{\phi}_{F,\text{eff}}^{\mathcal{Q}}\right) \leq (1-\theta)^2,$$

then (69) holds throughout the feasible set. Hence

$$\frac{\theta(\phi_B^{BO}+\phi_F^{BO}) - \phi_B^{BO}\phi_F^{BO}}{2\theta-1} \geq 1 > \overline{\phi}^{LO}(K),$$

which implies that credit availability expands for every feasible borrower-ownership equilibrium precision pair satisfying the lower-bound condition. If this condition fails,

the lower bounds alone do not determine the sign of the credit effect, and credit expansion is given by the threshold comparison in (53).

Q.E.D.

IA.1.8 Proof of Proposition 7

Fix total data M. Under the endogenous-share specification, the bank chooses $x \in [0,1]$, with $I = xM$ and $K = (1-x)M$. The choice of x therefore induces a one-dimensional feasibility curve

$$\Gamma_M = \{(\phi_B(x;M), \phi_F(x;M)) : x \in [0,1]\}.$$

The blind bid region requires $\lambda_B(x;M)\lambda_F(x;M) < \lambda_\theta(R-1)$. At $x = 0$, the reverse weak inequality follows from $(\phi_B(0;M), 1/2) \notin \mathcal{B}$. Because both precisions, and hence both likelihood ratios, increase with x, the curve cannot subsequently enter $\mathcal{B}$.

Restricting attention to equilibrium-relevant bank-advantage choices, the bank's borrower-ownership problem can be written as

$$\Psi_B^{BO}(x;M) = \begin{cases} \mathbb{E}[\Pi_B^E \mid x, M], & (\phi_B(x;M), \phi_F(x;M)) \in \mathcal{Q}, \\ \Pi_B^{NE}(x,M), & (\phi_B(x;M), \phi_F(x;M)) \in \mathcal{D}. \end{cases}$$

If $\Gamma_M \cap \mathcal{D} = \emptyset$, the equilibrium lies in $\mathcal{Q}$, where the fintech enters. The bank's payoff along the induced curve has derivative

$$\frac{\mathrm{d}}{\mathrm{d}x}\mathbb{E}[\Pi_B^E \mid x, M] = \frac{\partial \mathbb{E}[\Pi_B^E]}{\partial \phi_B}\frac{\partial \phi_B(x;M)}{\partial x} + \frac{\partial \mathbb{E}[\Pi_B^E]}{\partial \phi_F}\frac{\partial \phi_F(x;M)}{\partial x}.$$

On the bank-advantage portion of $\mathcal{Q}$, $\partial\mathbb{E}[\Pi_B^E]/\partial\phi_B > 0$ and $\partial\mathbb{E}[\Pi_B^E]/\partial\phi_F < 0$. Consequently, the derivative has the same sign as

$$-\frac{\partial \mathbb{E}[\Pi_B^E]/\partial\phi_B}{\partial \mathbb{E}[\Pi_B^E]/\partial\phi_F} - \frac{\partial\phi_F(x;M)/\partial x}{\partial\phi_B(x;M)/\partial x}.$$

The first term is the slope of the bank's iso-profit curve, and the second is the slope of Γ_M. By the relative-convexity condition in the proposition, the latter can cross the former at

most once, from below. The bank's marginal payoff can therefore cross zero at most once, from positive to negative. If the marginal payoff at $x = 0$ is nonpositive, it is negative thereafter, and the optimum is $x = 0$. If the marginal payoff at $x = 1$ is nonnegative, it is positive beforehand, and the optimum is $x = 1$. Otherwise, continuity yields a unique interior zero of the marginal payoff, which is the unique interior optimum. As in the proof of Proposition 2, any fintech-advantage tail cannot create an additional optimum.

If $\Gamma_M \cap \mathcal{D} \neq \emptyset$, Corollary 1 implies that any feasible deterrence-region point yields a strictly higher bank payoff than any accommodation-region point. Thus the optimum must lie in $\mathcal{D}$. Within $\mathcal{D}$, the fintech does not enter and the bank's monopoly payoff is strictly increasing in its own precision ϕ_B. Since the maintained endogenous-share assumptions imply that ϕ_B is increasing along the relevant part of Γ_M, the bank chooses the largest x that keeps the induced precision pair in $\mathcal{D}$:

$$x_B^{BO}(M) = \max\{x \in [0,1] : (\phi_B(x;M), \phi_F(x;M)) \in \mathcal{D}\}.$$

The maximum exists because the induced curve is continuous and the deterrence region is closed. This rule includes corner solutions. It gives $x = 0$ if the all-non-portable allocation is the rightmost deterrence point and $x = 1$ if full portability remains in the deterrence region. If $x = 0$ lies strictly inside the deterrence region, continuity implies that some positive portable shares also deter entry; because the bank's monopoly payoff rises with x, the optimum is then strictly positive. Thus, the fact that $x = 0$ itself deters entry does not generally make it optimal.

The deterrence argument uses only Corollary 1 and the monotonicity of ϕ_B in x; it requires neither the no-blind-bidding restriction nor the relative-convexity condition, and hence applies whenever $\Gamma_M \cap \mathcal{D} \neq \emptyset$. This proves the result. *Q.E.D.*

IA.1.9 Proof of Lemma 5

Fix an active entrant count $m \in \{1, \ldots, N\}$. Let the m active fintech signals be conditionally independent given the borrower's type, each with precision ϕ_F. After the worst signal profile, in which the bank and all active fintechs receive bad signals, the posterior

probability of success is

$$\pi^{b,b^m} = \frac{\theta(1-\phi_B)(1-\phi_F)^m}{\theta(1-\phi_B)(1-\phi_F)^m + (1-\theta)\phi_B\phi_F^m}.$$

Therefore the effective upper bound of the bidding support is

$$\bar{r}_m = \min\{R, 1 + \lambda_\theta^{-1}\lambda_B\lambda_F^m\}.$$

It remains to characterize the active fintechs' expected entry payoff after good signals. Let ℓ denote the net lower bound of the good-signal bidding support. The fintech zero-profit lower bound is

$$\ell_F = \frac{(1-\theta)(1-\phi_F)}{\theta\phi_F} = \lambda_\theta^{-1}\lambda_F^{-1}.$$

The bank's indifference condition with m active fintech competitors gives

$$\ell_B^{(m)} = (\bar{r}_m - 1)(1-\phi_F)^m + \frac{1}{\lambda_\theta\lambda_B}\left(1-\phi_F^m\right),$$

which generalizes the two-lender construction in Online Appendix IA.2. Multiplying the difference $(\ell_B^{(m)} - \ell_F)$ by the positive scalar λ_θ gives exactly the m-entry support index

$$\Delta_l^{(m)} = \lambda_\theta(\bar{r}_m - 1)(1-\phi_F)^m + \lambda_B^{-1}(1-\phi_F^m) - \lambda_F^{-1}.$$

Thus $\Delta_l^{(m)}$ has the same sign as an active fintech's expected entry payoff conditional on exactly m active fintech lenders.

Next fix (ϕ_B, ϕ_F, R) and consider how this payoff changes with the active entrant count m. The index $\Delta_l^{(m)}$ is increasing in $\bar{r}_m$, and

$$\bar{r}_m = \min\{R, 1 + \lambda_\theta^{-1}\lambda_B\lambda_F^m\}.$$

Therefore

$$\Delta_l^{(m)} = \min\left\{\Delta_l^{\mathrm{NB},(m)}, \Delta_l^{\mathrm{BB},(m)}\right\},$$

where

$$\Delta_l^{\mathrm{NB},(m)} = \lambda_\theta(R-1)(1-\phi_F)^m + \lambda_B^{-1}(1-\phi_F^m) - \lambda_F^{-1},$$

evaluates the index at $\bar{r}_m = R$, and

$$\Delta_l^{\mathrm{BB},(m)} = \lambda_B \phi_F^m + \lambda_B^{-1}(1-\phi_F^m) - \lambda_F^{-1}$$

evaluates the index at $\bar{r}_m = 1 + \lambda_\theta^{-1}\lambda_B\lambda_F^m$.

Consider first the nonblind branch. Using $\phi_F = \lambda_F/(1+\lambda_F)$ and $1-\phi_F = 1/(1+\lambda_F)$, the condition $\Delta_l^{\mathrm{NB},(m)} > 0$ is equivalent to

$$\lambda_\theta(R-1) > T_m(\lambda_B, \lambda_F),$$

where

$$T_m(\lambda_B, \lambda_F) = (\lambda_F^{-1} - \lambda_B^{-1})(1+\lambda_F)^m + \lambda_B^{-1}\lambda_F^m.$$

Since $1 > \phi_B > 1/2$ and $\phi_B \geq \phi_F \geq 1/2$, we have $\lambda_B > 1$ and $\lambda_B \geq \lambda_F \geq 1$, so

$$T_{m+1}(\lambda_B, \lambda_F) - T_m(\lambda_B, \lambda_F) = (\lambda_F^{-1} - \lambda_B^{-1})\lambda_F(1+\lambda_F)^m + \lambda_B^{-1}\lambda_F^m(\lambda_F - 1) > 0,$$

where strictness uses $\lambda_B > 1$ (the first term is positive when $\lambda_F = 1$, the second when $\lambda_F > 1$). Thus the set $\{m : \Delta_l^{\mathrm{NB},(m)} > 0\}$ is an initial segment.

On the blind-bidding branch,

$$\Delta_l^{\mathrm{BB},(m)} = (\lambda_B - \lambda_B^{-1})\phi_F^m + \lambda_B^{-1} - \lambda_F^{-1}.$$

Since $\lambda_B > 1$ and $0 < \phi_F < 1$, this expression is strictly decreasing in m. Hence $\{m : \Delta_l^{\mathrm{BB},(m)} > 0\}$ is also an initial segment.

Finally,

$$\{m : \Delta_l^{(m)} > 0\} = \{m : \Delta_l^{\mathrm{NB},(m)} > 0\} \cap \{m : \Delta_l^{\mathrm{BB},(m)} > 0\}.$$

The intersection of two initial segments is an initial segment, proving that the supportable active counts form an initial segment of $\{1, \ldots, N\}$.

Now fix $m_0 \in \{2, \ldots, N\}$ and suppose $\Delta_l^{(m_0)} = 0$. Because $\Delta_l^{(m_0)}$ equals the minimum of the nonblind and blind-bidding branch indexes, both branch indexes are weakly positive at m_0, and at least one is zero. The strict increase of $T_m(\lambda_B, \lambda_F)$ implies $\Delta_l^{\mathrm{NB},(m_0-1)} > 0$; the strict decrease of $\Delta_l^{\mathrm{BB},(m)}$ in m implies $\Delta_l^{\mathrm{BB},(m_0-1)} > 0$. Therefore $\Delta_l^{(m_0-1)} > 0$. Since the

positive-support set is an initial segment and m_0 itself is not in that set, $\Delta_l^{(k)} \leq 0$ for every $k > m_0$. Using the sign equivalence above, exactly m_0 active fintechs break even, $m_0 - 1$ active fintechs earn strictly positive expected entry payoffs, and any larger active entrant count yields weakly nonpositive expected entry payoffs for the active fintechs. *Q.E.D.*

IA.1.10 Proof of Proposition 8

We first verify the claim used in the text on the bank-advantage portion of the path. On the nonblind branch,

$$\Delta_l^{\mathrm{NB},(2)} = (1-\phi_F)\left[\lambda_\theta(R-1)(1-\phi_F) + \lambda_B^{-1}(1+\phi_F) - \frac{1}{\phi_F}\right].$$

Equation (3) and monotonicity imply $\lambda_B > \lambda_\theta(R-1)$, so $\lambda_B^{-1} < [\lambda_\theta(R-1)]^{-1}$. If $\lambda_F \leq \lambda_\theta(R-1)$, substitution of this upper bound makes the bracket weakly negative. If $\lambda_F > \lambda_\theta(R-1)$, bank advantage gives $\lambda_B^{-1} \leq (1-\phi_F)/\phi_F$, and the bracket is bounded above by

$$\lambda_\theta(R-1)(1-\phi_F) - \phi_F < 0.$$

Because $\Delta_l^{(2)}$ is the minimum of its nonblind and blind-branch expressions, it follows that $\Delta_l^{(2)} \leq 0$ throughout the bank-advantage portion. Equation (61) imposes the same inequality on any remaining tail.

Lemma 5 then implies that no outcome with two or more active fintechs can be sustained at any I. If the one-fintech benchmark has $\Delta_l^{(1)} > 0$, a no-entry outcome cannot be an equilibrium because any one fintech can profitably enter; there are instead N symmetric equilibria with exactly one entrant. If $\Delta_l^{(1)} \leq 0$, the arbitrarily small positive entry cost and the nonentry tie-break imply that no fintech enters. Thus the number of entrants at every data choice is exactly the number in the one-fintech benchmark. The bank consequently faces the same continuation payoff at every I and chooses the same portable-data production. *Q.E.D.*

IA.2 Lending Competition Equilibrium

This appendix provides the detailed characterization of the lending competition equilibrium that underlies Proposition 1. We solve the lending subgame for any fixed pair of signal precisions (ϕ_B, ϕ_F), conditional on fintech entry. Because the model is symmetric, we focus on the case $\phi_B \geq \phi_F$.

IA.2.1 Posterior beliefs

Recall that the prior probability of a high-type borrower is $\theta = \Pr(H)$. The lenders receive signals $s_B, s_F \in \{g, b\}$ with accuracy ϕ_B and ϕ_F, respectively. Let the prior odds and the likelihood ratios for the signals be the following.

$$\lambda_B = \frac{\phi_B}{1-\phi_B}, \qquad \lambda_F = \frac{\phi_F}{1-\phi_F}, \qquad \lambda_\theta = \frac{\theta}{1-\theta}. \tag{70}$$

For $i, j \in \{g, b\}$, let

$$\pi^{ij} \equiv \Pr\left(X = R \mid s_B = i,\ s_F = j\right), \tag{71}$$

that is, the posterior belief that $X = R$ conditional on the bank receiving signal i and the fintech receiving signal j.

Using Bayes' rule, we have

$$\pi^{gg} = \frac{\lambda_B \lambda_F \lambda_\theta}{1 + \lambda_B \lambda_F \lambda_\theta}, \qquad \pi^{gb} = \frac{\lambda_B \lambda_F^{-1} \lambda_\theta}{1 + \lambda_B \lambda_F^{-1} \lambda_\theta}, \tag{72}$$

$$\pi^{bg} = \frac{\lambda_B^{-1} \lambda_F \lambda_\theta}{1 + \lambda_B^{-1} \lambda_F \lambda_\theta}, \qquad \pi^{bb} = \frac{\lambda_B^{-1} \lambda_F^{-1} \lambda_\theta}{1 + \lambda_B^{-1} \lambda_F^{-1} \lambda_\theta}. \tag{73}$$

To see this explicitly for π^{gg}, applying Bayes' rule yields:

$$\begin{aligned} \pi^{gg} &= \frac{\Pr(s_B = g, s_F = g \mid H)\Pr(H)}{\Pr(s_B = g, s_F = g \mid H)\Pr(H) + \Pr(s_B = g, s_F = g \mid L)\Pr(L)} \\ &= \frac{\phi_B \phi_F \theta}{\phi_B \phi_F \theta + (1-\phi_B)(1-\phi_F)(1-\theta)}. \end{aligned}$$

Dividing the numerator and denominator by $(1-\phi_B)(1-\phi_F)(1-\theta)$ directly produces

$\pi^{gg} = \frac{\lambda_B\lambda_F\lambda_\theta}{\lambda_B\lambda_F\lambda_\theta+1}$. The cases for (gb), (bg), and (bb) follow identical steps by replacing the corresponding signal's factor with $(1-\phi_\cdot)$ in the likelihood under H and the complementary factor under L.

IA.2.2 Proof of Lemma 1

Recall the payoff indexes defined in the main text:

$$\Delta_s \equiv \pi^{bb}R - 1 = \frac{\lambda_\theta(R-1) - \lambda_B\lambda_F}{\lambda_\theta + \lambda_B\lambda_F}, \tag{74}$$

$$\Delta_l \equiv \lambda_\theta(\bar{r}-1)(1-\phi_F) + \lambda_B^{-1}(1-\phi_F) - \lambda_F^{-1}, \qquad \bar{r} = \min\{R, 1+\lambda_B\lambda_F\lambda_\theta^{-1}\}. \tag{75}$$

The equation $\Delta_s = 0$ defines the blind-bidding boundary.

On the nonblind-bidding branch, $\bar{r} = R$. In that case, $\Delta_l = 0$ is equivalent to

$$R = 1 + \lambda_\theta^{-1} + \left(\lambda_F^{-1} - \lambda_B^{-1}\right)\lambda_\theta^{-1} \equiv R_l.$$

Thus, on this branch, $\Delta_l > 0$ if and only if $R > R_l$.

To show that the payoff-index partition is well-defined in the one-fintech benchmark, it remains to show that the blind-bidding boundary lies above the entry-deterrence boundary for any informative signals ($\phi_B > 1/2$ and $\phi_F > 1/2$, which imply $\lambda_B > 1$ and $\lambda_F > 1$). Let us compare the blind-bidding break-even return with R_l:

$$\begin{aligned}\left(1+\lambda_B\lambda_F\lambda_\theta^{-1}\right) - R_l &= \left(1+\lambda_B\lambda_F\lambda_\theta^{-1}\right) - \left(1+\lambda_\theta^{-1} + (\lambda_F^{-1} - \lambda_B^{-1})\lambda_\theta^{-1}\right) \\ &= \lambda_\theta^{-1}\left(\lambda_B\lambda_F - 1 - \lambda_F^{-1} + \lambda_B^{-1}\right).\end{aligned}$$

Since the prior odds $\lambda_\theta > 0$, the sign of this difference depends entirely on the term in the parentheses. Let $f(\lambda_B, \lambda_F) \equiv \lambda_B\lambda_F - 1 - \lambda_F^{-1} + \lambda_B^{-1}$. For any fixed $\lambda_B > 1$, the partial derivative of f with respect to λ_F is:

$$\frac{\partial f(\lambda_B, \lambda_F)}{\partial \lambda_F} = \lambda_B + \lambda_F^{-2} > 0. \tag{76}$$

Because f is strictly increasing in λ_F, and given that informative signals require $\lambda_F > 1$,

we have:

$$\begin{aligned} f(\lambda_B, \lambda_F) > f(\lambda_B, 1) &= \lambda_B(1) - 1 - 1^{-1} + \lambda_B^{-1} \\ &= \lambda_B - 2 + \frac{1}{\lambda_B} \\ &= \frac{\lambda_B^2 - 2\lambda_B + 1}{\lambda_B} \\ &= \frac{(\lambda_B - 1)^2}{\lambda_B}. \end{aligned}$$

Since $\lambda_B > 1$, it strictly follows that $\frac{(\lambda_B-1)^2}{\lambda_B} > 0$. Thus, $f(\lambda_B, \lambda_F) > 0$ for all $\lambda_B > 1, \lambda_F > 1$, which implies that the blind-bidding break-even return exceeds R_l everywhere in the relevant parameter space.

Because the blind-bidding break-even return exceeds R_l strictly, the deterrence region does not overlap with the blind bid region. Suppose $\Delta_s > 0$, so that $R > 1 + \lambda_B \lambda_F \lambda_\theta^{-1}$ and the economy lies on the blind-bidding branch, where $\bar{r} = 1 + \lambda_B \lambda_F \lambda_\theta^{-1}$. On this branch Δ_l coincides with the nonblind expression evaluated at $1 + \lambda_B \lambda_F \lambda_\theta^{-1}$, so $\Delta_l > 0$ if and only if this break-even return exceeds R_l, which holds. Hence $\Delta_s > 0$ implies $\Delta_l > 0$ in the one-fintech benchmark, and the guarded payoff-index partition is equivalent to the familiar threshold partition:

$$\mathcal{D} \quad : \quad \Delta_l \leq 0, \tag{77}$$

$$\mathcal{Q} \quad : \quad \Delta_l > 0 \text{ and } \Delta_s \leq 0, \tag{78}$$

$$\text{blind bid region} \quad : \quad \Delta_l > 0 \text{ and } \Delta_s > 0. \tag{79}$$

These three regions are mutually exclusive and exhaustive by construction.

IA.2.3 Detailed equilibrium in the accommodation region

Suppose $\Delta_l > 0$ and $\Delta_s \leq 0$. Then neither lender bids after a bad signal:

$$\beta_B(b) = \beta_F(b) = \infty. \tag{80}$$

After a good signal, both lenders participate with probability one and mix over a common support $[l_{\mathcal{Q}}, R-1]$, where

$$1 + l_{\mathcal{Q}} = \frac{R}{1+\lambda_F} + \frac{\lambda_F}{1+\lambda_F}\frac{1}{\pi^{gg}}. \tag{81}$$

Let $\overline{G}_B^g(r)$ and $\overline{H}_F^g(r)$ denote the survival functions of the bank's and fintech's mixed strategies after receiving a good signal. For $r \in [l_{\mathcal{Q}}, R-1]$, they satisfy

$$\overline{G}_B^g(r) = \frac{\lambda_F\lambda_\theta\left(\left(1+\lambda_B\right)l_{\mathcal{Q}} - r\right) - 1}{\lambda_B\lambda_F\lambda_\theta r - 1}, \tag{82}$$

$$\overline{H}_F^g(r) = \frac{\lambda_B\lambda_\theta\left(\left(1+\lambda_F\right)l_{\mathcal{Q}} - r\right) - 1}{\lambda_B\lambda_F\lambda_\theta r - 1}. \tag{83}$$

The lenders' expected payoffs conditional on receiving a good signal are

$$\overline{\Pi}_B^g = \frac{1}{1+\lambda_B^{-1}\lambda_\theta^{-1}}\left(1+l_{\mathcal{Q}}\right) - 1, \tag{84}$$

$$\overline{\Pi}_F^g = \frac{1}{1+\lambda_F^{-1}\lambda_\theta^{-1}}\left(1+l_{\mathcal{Q}}\right) - 1. \tag{85}$$

Both are strictly positive. Therefore, the fintech's expected payoff from entry is strictly positive, so it enters.

The bank's ex-ante profit in the accommodation region is

$$\begin{aligned}\Pi_{B,\mathcal{Q}}^E &= \frac{\lambda_B\lambda_\theta(R-1) - \lambda_F}{(1+\lambda_B)(1+\lambda_F)(1+\lambda_\theta)} \\ &= \theta(R-1)\phi_B\left(1-\phi_F\right) - (1-\theta)\phi_F\left(1-\phi_B\right)\end{aligned} \tag{86}$$

$$\nabla\Pi_{B,\mathcal{Q}}^E(\phi_B,\phi_F) = \begin{bmatrix}\Pi_{B,\phi_B}^E \\ \Pi_{B,\phi_F}^E\end{bmatrix} = \begin{bmatrix}\theta\left(R-1\right)\left(1-\phi_F\right) + \left(1-\theta\right)\phi_F \\ -\theta\left(R-1\right)\phi_B - \left(1-\theta\right)\left(1-\phi_B\right)\end{bmatrix}.$$

$$\nabla^2\Pi_{B,\mathcal{Q}}^E(\phi_B,\phi_F) = \begin{bmatrix}\Pi_{B,\phi_B\phi_B}^E & \Pi_{B,\phi_B\phi_F}^E \\ \Pi_{B,\phi_F\phi_B}^E & \Pi_{B,\phi_F\phi_F}^E\end{bmatrix} = \begin{bmatrix}0 & 1-\theta R \\ 1-\theta R & 0\end{bmatrix}.$$

IA.2.4 Detailed equilibrium in the deterrence region

Suppose $\Delta_l \leq 0$. As in the accommodation region, neither lender bids after a bad signal:

$$\beta_B(b) = \beta_F(b) = \infty. \tag{87}$$

In the interior of the deterrence region, the less-informed lender participates with probability strictly below one after receiving a good signal; on the boundary, it participates with probability one. The relevant lower bound is

$$1 + \tilde{l}_F = 1 + \lambda_F^{-1}\lambda_\theta^{-1}. \tag{88}$$

The bank always bids after a good signal. The fintech bids after a good signal with probability

$$m_F^g = \frac{(1+\lambda_F^{-1})\left(R - 1 - \lambda_F^{-1}\lambda_\theta^{-1}\right)}{R - 1 - \lambda_B^{-1}\lambda_F^{-1}\lambda_\theta^{-1}} \in (0, 1]. \tag{89}$$

Here $m_F^g = 1$ on the entry-deterrence boundary and $m_F^g < 1$ in the interior of the deterrence region.

For $r \in [\tilde{l}_F, R-1]$, the bank's and fintech's survival functions are

$$\overline{G}_B^g(r) = \frac{\lambda_F\lambda_\theta\left((1+\lambda_B)\,\tilde{l}_F - r\right) - 1}{\lambda_B\lambda_F\lambda_\theta r - 1}, \tag{90}$$

$$\overline{H}_F^g(r) = \frac{1}{m_F^g}\frac{\lambda_B\lambda_\theta\left((1+\lambda_F)\,\tilde{l}_F - r\right) - 1}{\lambda_B\lambda_F\lambda_\theta r - 1} - \frac{1 - m_F^g}{m_F^g}. \tag{91}$$

The lenders' expected payoffs conditional on receiving a good signal are

$$\overline{\Pi}_B^g = \frac{1}{1+\lambda_B^{-1}\lambda_\theta^{-1}}\left(1 + \tilde{l}_F\right) - 1 = \frac{1+\lambda_F^{-1}\lambda_\theta^{-1}}{1+\lambda_B^{-1}\lambda_\theta^{-1}} - 1, \tag{92}$$

$$\overline{\Pi}_F^g = 0. \tag{93}$$

Hence the fintech's expected payoff from entry is zero, so with arbitrarily small entry cost it does not enter in equilibrium.

IA.2.5 Blind bid region for completeness

For completeness, suppose $\Delta_s > 0$. Then both lenders bid even after a bad signal:

$$\beta_B(b) = \beta_F(b) = \frac{1}{\pi^{bb}} - 1. \tag{94}$$

After a good signal, both lenders mix over a common support $[l_I, u_I]$, where

$$1 + u_I = \frac{1}{\pi^{bb}}, \tag{95}$$

$$1 + l_I = \frac{1}{1+\lambda_F}(1 + u_I) + \frac{\lambda_F}{1+\lambda_F}\frac{1}{\pi^{gg}}. \tag{96}$$

Let $\overline{G}_B^g(r)$ and $\overline{H}_F^g(r)$ denote the survival functions of the bank's and fintech's mixed strategies after receiving a good signal. The bank's distribution includes a point mass $q_B = \frac{\lambda_B - \lambda_F}{\lambda_B(1+\lambda_F)}$ at the upper bound u_I. For $r \in [l_I, u_I)$, they satisfy

$$\overline{G}_B^g(r) = \frac{\lambda_F \lambda_\theta \left((1+\lambda_B) l_I - r\right) - 1}{\lambda_B \lambda_F \lambda_\theta r - 1}, \tag{97}$$

$$\overline{H}_F^g(r) = \frac{\lambda_B \lambda_\theta \left((1+\lambda_F) l_I - r\right) - 1}{\lambda_B \lambda_F \lambda_\theta r - 1}. \tag{98}$$

The lenders' expected payoffs conditional on receiving a good signal are

$$\overline{\Pi}_B^g = \frac{1}{1 + \lambda_B^{-1}\lambda_\theta^{-1}}(1 + l_I) - 1, \tag{99}$$

$$\overline{\Pi}_F^g = \frac{1}{1 + \lambda_F^{-1}\lambda_\theta^{-1}}(1 + l_I) - 1. \tag{100}$$

This region is ruled out by the maintained assumptions in the main text, but it completes the global characterization of lending competition for arbitrary signal-precision pairs.

IA.2.6 Monopoly benchmark

If the fintech does not enter, the bank is a monopoly lender. Its unique pure strategy is

$$\beta_B(b) = \infty, \qquad \beta_B(g) = R - 1. \tag{101}$$

The bank's expected payoff after a good signal is

$$\overline{\Pi}_B^g \;=\; \frac{1}{\lambda_B^{-1}\lambda_\theta^{-1} + 1} R - 1 > 0 \tag{102}$$

Thus, the bank lends only after receiving a good signal and charges the highest feasible rate.