Screening with Price and Data: Adverse Selection and Information Heterogeneity in Search Markets*

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Abstract

We study adverse selection in a search market where a lender obtains data on borrowers and can condition acceptance on this information. The lender posts contracts, each specifying price, expected queue length, and applicant composition, while borrowers choose where to queue endogenously. After matching, the lender observes a noisy signal of borrower type and decides ex post whether to trade. The model delivers three equilibrium regimes: separating, pooling with selective acceptance, and autarky. Screening occurs purely through price in the separating regime but also through data in the pooling regime. We calibrate the model to a Fintech lender who uses alternative data, targeting its area under the curve, interest rate, loan approval, and default rates, and analyze optimal contracts for traditional banks and e-commerce lenders. Counterfactuals from the calibrated model show that, counterintuitively, better data can raise default rates when Fintech lenders optimally serve applicant pools with lower average quality.

Keywords: Search Frictions, Asymmetric Information, Classification, Fintech, Credit, Alternative Data

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1 Introduction

In many search markets, including credit, labor, and housing, buyers acquire data during bilateral meetings to infer seller quality. These data range from credit scores to criminal background and digital footprints, and their informativeness often varies across buyers. When both price-based and data-based screening are available, an important question arises: Do buyers screen with price or with data?

We study this question in the context of credit markets. A lender posts contracts, each consisting of a price, an expected borrower distribution, and a queue length. Borrowers, who are privately informed about their type (good or bad), choose whether and where to apply, forming endogenous queues. Upon matching, the lender observes a signal about the borrower's type and chooses whether to accept or reject the trade on the basis of this information. Crucially, acceptance decisions are made ex post and cannot be contractually committed to in advance.[1]

A key innovation of this paper is the introduction of a simple information structure that produces a smooth, strictly concave Receiver Operating Characteristic (ROC) curve,

$$\text{True Positive Rate} = \text{False Positive Rate}^{\,1-a}, \tag{1}$$

where the true and false positive rates correspond to the acceptance probabilities of good and bad borrowers, respectively.[2] This ROC curve closely matches those observed empirically in credit markets (Iyer, Khwaja, Luttmer, and Shue, 2016; Vallee and Zeng, 2019; Berg, Burg, Gombović, and Puri, 2020). The informativeness parameter a, which governs the extent of *cross-subsidization* in eligible pooling contracts, can be directly calibrated from the Area Under the ROC Curve (AUC), a standard empirical measure of data quality.

We define lender selectiveness as

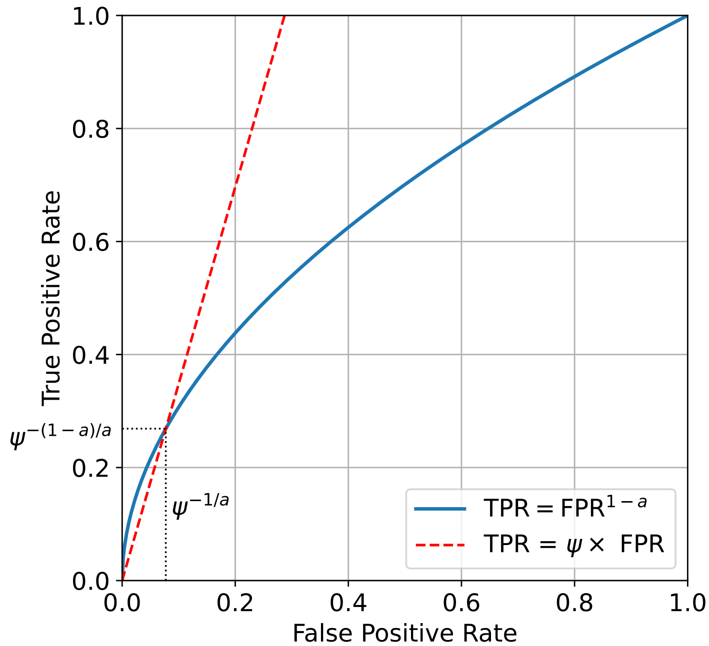
$$\psi = \frac{\text{True Positive Rate}}{\text{False Positive Rate}}.$$

Figure 1 shows the ROC curve and its intersection with the ray corresponding to a fixed ψ. A higher ψ moves the intersection inward along the curve: acceptance becomes more selective, reducing acceptance probabilities for both types but more sharply for bad borrowers.

[1] If the lender can commit only to the ex-post optimal acceptance rule, the results are unchanged. With general commitment, however, pooling contracts disappear due to a profitable deviation to an otherwise identical separating contract consisting solely of good borrowers, although lenders continue to screen with data in separating contracts due to prior commitment.

[2] In this paper, we define the positive class as the good outcome to simplify exposition. Some studies instead take the bad outcome as positive. Flipping the positive and negative classes mirrors the ROC curve across the anti-diagonal ($x + y = 1$) but leaves the area under the curve unchanged.

Figure 1: ROC Curve and Lender Selectiveness



Notes: The solid blue curve depicts the Receiver Operating Characteristic (ROC) curve implied by our information structure, which gives the maximum true positive rate achievable for each false positive rate. In our setting, these rates correspond to the acceptance probabilities of good and bad borrowers. The dashed red ray connects the origin to a point on the ROC curve, with its slope ψ defining lender selectiveness. Increasing ψ corresponds to moving inward along the ROC curve, which lowers the acceptance probabilities of both good and bad borrowers.

Consequently, the share of good borrowers among accepted matches rises with ψ. Ex-post, when the queue length and applicant composition are fixed, the lender faces a simple quantity–quality tradeoff when choosing ψ: greater selectiveness improves match quality but reduces the lender's trading probability. In equilibrium, however, borrower entry is endogenous. On the positive side, higher selectiveness allows a lower price, as data-based screening substitutes for screening through higher prices (and thus longer queues). On the negative side, greater selectiveness requires a worse applicant pool and reduces the lender's trading probability both directly (via a stricter acceptance rule) and indirectly (via a shorter equilibrium queue). The lender balances these effects when designing pooling contracts.

Our model can generate a rich set of equilibrium regimes. Holding other parameters fixed, as the participation cost of bad borrowers decreases, the economy transitions from separation to pooling and then to autarky. The lender screens purely with price in the separating regime but relies on both price and data in the pooling regime. These transitions are sharp: small parameter changes can trigger discontinuous jumps in prices and trading probabilities (market liquidity).

The existence of a pooling regime relies critically on informative data. When data are uninformative ($a = 0$), our model reverts back to Guerrieri, Shimer, and Wright (2010). In that case, pooling contracts vanish because a lender can profitably deviate to an otherwise identical separating contract that attracts only good borrowers, making separation the only sustainable regime. With informative data ($a > 0$), however, a pooling contract can involve selective acceptance. A deviation to an identical separating contract is no longer feasible: if only good borrowers applied, a deviating lender would have no incentive to screen with data, causing bad borrowers to re-enter. Hence, informative data can sustain a pooling regime that cannot arise when data are uninformative.

Our baseline model assumes a single lender, but it extends naturally to environments with many competitive lenders that differ in data informativeness, search technology, and valuation. This flexibility is crucial for our application to credit markets, where lenders make markedly different use of alternative data. Reported AUC values span a wide range, from about 60% for banks that rely solely on credit reports to nearly 90% for decentralized finance protocols that leverage rich on-chain histories, highlighting the substantial heterogeneity in data quality across lenders. Although we assume free entry for borrowers, reflecting the reality of credit markets, and therefore treat borrower market utilities as exogenous, the framework can also be adapted to settings where the supplies of borrowers are fixed. In that case, solving for the equilibrium requires an additional step in which borrower market utilities are determined from type-specific supplies through market-clearing conditions.

We calibrate the model to a leading Fintech lender, Upstart, targeting its area under the curve, interest rate, loan approval rate, and default rate as reported in Di Maggio, Ratnadiwakara, and Carmichael (2022). We then simulate counterfactuals for traditional banks and an e-commerce platform lender, which are reported to have lower and higher data informativeness, respectively, relative to Upstart. A higher a raises the optimal degree of selectiveness by reducing the quantity cost of screening, which through equilibrium adjustment leads to a lower price (higher interest rate) and a shorter queue. However, greater informativeness does not mechanically translate into a better pool of accepted borrowers. In pooling contracts, optimal acceptance requires that the posterior probability of a bad borrower at the cutoff, the break-even precision, equals the lender's profit margin. Better data lowers the price, which increases the margin and therefore raises the required break-even precision. Under our information structure, the odds of bad to good borrowers conditional on the signal being above the acceptance threshold equal $(1 - a)$ times the posterior odds at that threshold. As a result, a higher break-even precision can generate a *worse* pool of accepted borrowers in equilibrium, even as a increases. Counterfactuals from the calibrated model produce a non-monotonic relationship between informativeness and loan performance: Upstart, despite having more informative data, exhibits a higher default rate (4.1%) than traditional banks (3.9%), while the e-commerce lender achieves a lower default rate (3.7%) than both.

We further examine how search frictions shape the optimal pooling contract. A reduction in frictions through lower borrower matching elasticity makes selective acceptance more attractive. Selectiveness lowers the lender's meeting probability by reducing equilibrium queue length, but this cost diminishes when matching elasticity is low. In the limit case of a Leontief matching function (zero elasticity in the meaningful region), lenders choose the most selective acceptance rule. Through equilibrium adjustment, lower search frictions lead to lower prices, and a lower average quality of the applicant pool. In the model calibrated to Fintech lending, reducing search frictions by lowering the matching elasticity from 0.5 to 0.4 raises the loan APY from 22.0% to 22.8% and reduces the loan approval rate from 24.5% to 23.0%.

We also analyze the effect of the lender discount rate, which captures both the cost of capital and the management and operational expenses of issuing and servicing loans. A higher discount rate lowers the valuation of loan payment streams and makes lenders more selective, as the cost of rejection falls. This prediction aligns with empirical evidence, such as Kovner and Van Tassel (2022), who document that increases in lenders' cost of capital are associated with tighter credit standards.

Related Work This paper contributes to several strands of the literature. First, the paper advances the theory of search under asymmetric information by incorporating both price-based and data-driven screening. Prior work in this area, including Guerrieri, Shimer, and Wright (2010), Chang (2018), and Williams (2021), emphasizes screening through prices. Other papers, such as Zhu (2012), Lauermann and Wolinsky (2016), Kaya and Kim (2018), Fishman, Parker, and Straub (2024), and Agarwal, Grigsby, Hortaçsu, Matvos, Seru, and Yao (2024), study environments in which screening with price is infeasible and focus exclusively on screening with data. A third line of research, including Delacroix and Shi (2013), Lester, Shourideh, Venkateswaran, and Zetlin-Jones (2018), and Cai, Gautier, and Wolthoff (2025), considers both price-based and data-driven screening but relies on binary signals and exogenous acceptance rules. We analyze a search environment in which lenders choose between screening with price or screening with data, and we adopt a smooth, empirically motivated information structure that allows lenders to set acceptance thresholds based on posted prices and on the composition of the applicant pool.[3] This richer framework makes it possible to study how search frictions and data informativeness jointly shape the selectiveness of acceptance, two dimensions not explored

[3] See Berg, Burg, Gombović, and Puri (2020) for evidence that lenders set acceptance thresholds so that the expected default rate at the threshold matches their profit margin.

in these earlier papers.

Second, our paper contributes to the literature on search frictions in credit markets, such as Wasmer and Weil (2004), Petrosky-Nadeau and Wasmer (2013), and Gabrovski and Ortego-Marti (2025). While these studies model credit markets using search-and-bargaining frameworks, they abstract from borrower default and data-based screening by lenders. In contrast, we study a price posting environment in which lenders can screen using data. We show that search frictions and data-based screening interact in economically meaningful ways: specifically, search frictions reduce lenders' selectiveness, leading to looser lending standards.

Third, our paper contributes to the growing empirical literature on Fintech. Recent studies show that Fintech lenders improve credit risk assessment by incorporating alternative data such as digital footprints, device metadata, and employment records (Iyer, Khwaja, Luttmer, and Shue, 2016; Vallee and Zeng, 2019; Berg, Burg, Gombović, and Puri, 2020; Di Maggio, Ratnadiwakara, and Carmichael, 2022). Yet, as Berg, Fuster, and Puri (2022) emphasize, evidence on the relative performance of Fintech and bank loans is mixed (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Di Maggio and Yao, 2021): some studies find comparable or better outcomes for Fintech lenders, while others document higher delinquency rates. We introduce a tractable model in which data informativeness maps directly into empirical metrics such as the AUC of credit risk models. Our framework provides a unified explanation for why data-rich lenders may accept worse borrowers and exhibit higher default rates. These outcomes arise endogenously through optimal contract design and applicant sorting, rather than reflecting a failure in the screening technologies employed by Fintech lenders.

Finally, our framework complements the literature on adverse selection in non-exclusive markets, such as Kurlat (2016) and Asriyan and Vanasco (2024), among others. Kurlat (2016) and Asriyan and Vanasco (2024) assume non-exclusive markets, which leads to pooling as the unique equilibrium outcome. In contrast, our model imposes market exclusivity, giving rise to a phase transition between separating and pooling equilibrium regimes. The two approaches also differ in how data informativeness influences the quality of accepted trades. In Kurlat (2016), a "least-restrictive-clears-first" algorithm ensures that lenders with greater data informativeness acquire higher-quality assets. In our model, however, expert lenders may optimally serve worse applicant pools and purchase a larger share of bad assets. This prediction is consistent with empirical evidence from Fintech lending, where lenders with superior access to alternative data sometimes experience higher default rates.

Outline The paper proceeds as follows. Section 2 introduces the basic environment, details our information structure, and defines equilibrium. Section 3 derives optimal separating and pooling contracts and compares equilibrium outcomes with and without informative data. Section 4 calibrates the model to Fintech lenders and traditional banks. Section 5 concludes.

2 Model

Basics There is a single lender with fixed capacity and a large mass of borrowers, who can be either good (g) or bad (b). Good borrowers have unit repayment capacity and face a cost c, while the lender values repayment at v. We assume the lender is more patient than borrowers, so $v > c$, ensuring that trading with a good borrower yields a strictly positive gain from trade. Bad borrowers, in contrast, have zero repayment capacity, incur no cost, and generate zero gains from trade.

Borrowers are privately informed about their types. The lender can post unit-capacity contracts, each consisting of three components: a price (or loan amount) p, an anticipated queue length θ, and an expected applicant composition γ. To enter the search market, borrowers must pay a participation cost $k(g)$ if good and $k(b)$ if bad, with both strictly positive. We assume the participation cost of good borrowers is below their gain from trade, $k(g) \in (0, v - c)$. For a given $k(g)$, a lower participation cost for bad borrowers $k(b)$ makes it harder to deter them from applying.

After observing all posted contracts, borrowers choose where to apply, generating endogenous queues. We assume a constant-returns-to-scale matching technology: for a contract with queue length θ, the lender's meeting probability $m(\theta)$ is increasing in θ, while each borrower's meeting probability

$$n(\theta) = \frac{m(\theta)}{\theta}$$

is decreasing in θ, with

$$\lim_{\theta \to 0} n(\theta) = 1.$$

During a bilateral meeting, the lender observes a signal, drawn from the type-dependent distributions F_g and F_b with densities f_g and f_b. Without loss of generality, we assume that the signal satisfies the monotone likelihood ratio property (MLRP).[4] Given the applicant composition $\gamma = (\gamma(g), \gamma(b))$, the lender's posterior belief after observing signal $\tilde{z}$ is

$$\bar{\gamma}(g) = \frac{\gamma(g)\, f_g(\tilde{z})}{\gamma(g)\, f_g(\tilde{z}) + \gamma(b)\, f_b(\tilde{z})}, \qquad \bar{\gamma}(b) = 1 - \bar{\gamma}(g).$$

[4]If the original signal does not satisfy MLRP, we can instead reinterpret the likelihood ratio $f_g(z)/f_b(z)$ as the signal, which by construction ensures MLRP.

The lender's profit from trade conditional on $\tilde{z}$ is

$$\bar{\gamma}(g)\, v - p,$$

which is strictly increasing in $\bar{\gamma}(g)$. Under MLRP, $\bar{\gamma}(g)$ is strictly increasing in $\tilde{z}$, so the optimal acceptance rule is a cutoff strategy: the lender accepts if and only if $\tilde{z}$ exceeds some threshold z.

Further Details As is standard in the literature, we assume that the matching function $m(\theta)$ is concave, and strictly concave whenever $m(\theta) < \min\{\theta, 1\}$. In addition, $m(\theta)$ has a well-defined elasticity, given by

$$\epsilon(\theta) = \frac{m'(\theta)\theta}{m(\theta)},$$

which exists everywhere except possibly at a finite number of points. Because the lender-side meeting probability increases and the borrower-side meeting probability decreases in θ, the elasticity satisfies $\epsilon(\theta) \in (0, 1)$.

We assume $\epsilon(\theta)$ is weakly decreasing in θ, so borrowers' relative contribution to matching falls as the queue length increases.[5] This standard assumption in the search literature holds for many, but not all, matching technologies (see Wright, Kircher, Julien, and Guerrieri (2021)), including the Leontief function $m(\theta) = \min\{\theta, 1\}$ and the Cobb–Douglas function $m(\theta) = \min\{\theta, A\theta^{\alpha}, 1\}$, with $0 < A, \alpha < 1$.

We normalize the signal distribution for bad borrowers to the standard uniform, $F_b(z) = z$ for $z \in [0, 1]$.[6] We assume the signal distribution for good borrowers is

$$F_g(z) = 1 - (1 - z)^{1-a},$$

where $a \in (0, 1)$ measures data informativeness. As a rises, the signal becomes more informative: when $a \to 0$, F_g coincides with the uniform distribution (uninformative data), while as $a \to 1$, it converges to a step function at 1 (perfectly informative data).[7]

To connect with the empirical literature, where data informativeness is commonly assessed using the Receiver Operating Characteristic (ROC) curve, we analyze these metrics under our

[5]This corresponds to the two sides being complements in the matching process, i.e., the matching function's elasticity of substitution is at most 1.

[6]This normalization is without loss of generality. If $z|b$ is not uniform, applying F_b to z yields a new signal that follows the standard uniform distribution.

[7]The informativeness of our assumed signal increases with a in the sense of Lehmann's informativeness ranking for monotone decision problems (Lehmann, 1988). We thank Shouyong Shi for pointing this out and for sharing his notes with us.

information structure. The ROC curve, a standard tool in binary classification, plots the true positive rate (TPR) against the false positive rate (FPR) as the acceptance threshold z varies.[8] In our setting, this corresponds to plotting $\bar{F}_g(z)$ against $\bar{F}_b(z) = 1 - F_b(z)$, the complementary cumulative distribution functions for good and bad types, respectively. A key summary statistic of the ROC curve is its AUC, a threshold-invariant measure of informativeness. Beyond its geometric meaning, the AUC captures the probability that the signal of a randomly chosen good borrower exceeds that of a randomly chosen bad borrower. Hence, the AUC measures how well the signal separates the two types.

Under our specification, the ROC curve takes the closed-form representation in (1), a power function that closely approximates the empirical ROC curves estimated for the credit market (Iyer, Khwaja, Luttmer, and Shue, 2016; Vallee and Zeng, 2019; Berg, Burg, Gombović, and Puri, 2020).[9] The AUC of our information structure is given by

$$\text{AUC} = \frac{1}{2-a}.$$

When $a \to 0$, AUC $= 50\%$ (uninformative data); when $a \to 1$, AUC $= 100\%$ (perfectly informative data).

Under our information structure, given threshold z, acceptance probabilities are $\bar{F}_g(z)$ and $\bar{F}_b(z)$. In the analysis, it is convenient to index the acceptance rule using

$$\psi \ = \ \frac{\bar{F}_g(z)}{\bar{F}_b(z)} \ = \ (1-z)^{-a} \ \geq 1,$$

instead of z. When $a \in (0,1)$, as z rises from 0 to 1, $\psi = (1-z)^{-a}$ increases from 1 to $+\infty$. Under this change of variable, the acceptance probability for good borrowers (TPR) is $\psi^{-(1-a)/a}$, while the acceptance probability for bad borrowers (FPR) is $\psi^{-1/a}$. At $\psi = 1$, all borrowers are accepted. As ψ increases, acceptance becomes less likely for both types, especially for bad borrowers. For this reason, a higher ψ reflects greater *selectiveness*.

Conditional on acceptance (that is, on observing $\tilde{z} \geq z$, or equivalently $(1-\tilde{z})^{-a} > \psi$), the composition of accepted borrowers is

$$\hat{\gamma}(g) = \frac{\gamma(g)\psi}{\gamma(g)\psi + \gamma(b)}, \qquad \hat{\gamma}(b) = 1 - \hat{\gamma}(g),$$

[8] The TPR and FPR are also referred to as sensitivity and 1-specificity, respectively.

[9] A commonly assumed information structure in the literature, particularly for binary types, is a binary signal. However, an implication of this assumption is a piecewise-linear ROC curve. In practice, ROC curves tend to exhibit a smooth, strictly concave shape, reflecting a more nuanced signal.

where $\hat{\gamma}(g)$ and $\hat{\gamma}(b)$ give the probabilities that an accepted borrower is good or bad, respectively.

Equilibrium Definition Let $Q = \{g, b\}$ and $\mathbb{P} = [c + k(g), v]$.[10] Q is the space of borrower types, and $\mathbb{P}$ includes all plausible trading prices. We now formally present the definition of equilibrium:

Definition 1. An *equilibrium* is a tuple (Ψ, V, Y, Y^*) consisting of an acceptance rule $\Psi : \mathbb{P} \times \Delta(Q) \to [1, \infty) \cup \{\infty\}$, the lender's profit $V \in \mathbb{R}_+$, a set of eligible contracts $Y \subset \bar{Y} = \mathbb{P} \times \Delta(Q) \times \mathbb{R}_+$ and a set of optimal contracts $Y^* \subset Y$. These objects must satisfy the following conditions:

C1. Optimal Acceptance: For any $(p, \gamma) \in \mathbb{P} \times \Delta(Q)$, the acceptance rule Ψ is chosen ex post to maximize the lender's matching surplus,

$$\Psi(p, \gamma) \in \arg\max_{\psi} \; \gamma(g)\psi^{-\frac{1-a}{a}}(v - p) \; - \; \gamma(b)\psi^{-\frac{1}{a}}p. \tag{2}$$

The resulting lender's surplus is

$$v(p, \gamma) = \gamma(g)\Psi(p, \gamma)^{-\frac{1-a}{a}}(v - p) \; - \; \gamma(b)\Psi(p, \gamma)^{-\frac{1}{a}}p,$$

and the borrowers' surpluses are given by

$$u(g; p, \gamma) = \Psi(p, \gamma)^{-\frac{1-a}{a}}\big(p - c\big), \qquad u(b; p, \gamma) = \Psi(p, \gamma)^{-\frac{1}{a}}p.$$

C2. Optimal Contract Posting: A contract (p, γ, θ) is eligible, i.e. $(p, \gamma, \theta) \in Y$, if

$$n(\theta)u(q; p, \gamma) \leq k(q) \quad \text{for all } q \in Q,$$

with equality whenever $\gamma(q) > 0$. Among all eligible contracts, the set of optimal contracts is defined by

$$Y^* = \arg\max_{(p,\gamma,\theta)\in Y} m(\theta)\, v(p, \gamma).$$

In equilibrium, the lender posts optimal contracts, so her profit

$$V = m(\theta)v(p, \gamma), \quad \text{for all } (p, \gamma, \theta) \in Y^*.$$

[10] We restrict attention to prices in $\mathbb{P}$. Any contract with a price below $c + k(g)$ is unacceptable to good borrowers, while any contract with a price above v is unacceptable to the lender. In either case, such a contract cannot be active in equilibrium.

Despite having only one lender, our equilibrium definition mirrors that of a competitive search equilibrium, where lenders take the market utilities of borrowers $k(\cdot)$ as given. C1 requires that a lender who posts a contract with price p and expected applicant composition γ chooses the selectiveness $\Psi(p, \gamma)$ to maximize her matching surplus. C2 imposes eligibility: contracts posted by the lender provide at most $k(q)$ to any borrower type q, and exactly $k(q)$ to those the lender expects to attract. The lender then selects the most profitable among these eligible contracts.

We include θ, the queue length of borrowers for the single lender, as part of the contract. However, it is isomorphic to treat θ as an endogenous equilibrium object that adjusts to satisfy the inequality in C2. Specifically, when the borrower surplus provided by a contract is large, more borrowers are attracted to apply, increasing the queue length. This, in turn, raises the lender's meeting probability but reduces the meeting probability for individual applicants.

3 Equilibrium

We begin the equilibrium analysis by characterizing the lender's optimal acceptance rule, as defined in condition C1. The first-order condition for problem (2) delivers the interior solution

$$\psi = \frac{\gamma(b)\, p}{(1-a)\, \gamma(g)\, (v-p)}. \tag{3}$$

This interior solution applies whenever the right-hand side exceeds one. In that case, the applicant composition is fully determined by the pair (ψ, p):

$$\gamma(g) = \Gamma(p, \psi) = \frac{p}{p + (1-a)\psi(v-p)}. \tag{4}$$

The intuition behind the result above comes from the break-even precision,

$$\bar{\gamma}(b) = 1 - \frac{p}{v}. \tag{5}$$

At the interior acceptance threshold, the lender must break even: the posterior probability of a bad borrower equals the lender's profit margin. This mirrors the finding in Berg, Burg, Gombović, and Puri (2020), who show that a platform lender sets its acceptance threshold so that the posterior default rate matches its profit margin. Under our information structure, the odds of bad to good borrowers in the prior distribution of applicants are $(1-a)\psi$ times the posterior odds,

$$\frac{\gamma(b)}{\gamma(g)} = (1-a)\, \psi\, \frac{\bar{\gamma}(b)}{\bar{\gamma}(g)}.$$

Substituting this expression into (5) yields (4). Higher selectiveness ψ requires a worse applicant composition because a worse prior can generate the same posterior under a more selective rule. A higher price requires a better applicant composition because it lowers the break-even precision, thereby requiring a better prior when ψ is fixed.

The lender chooses the corner solution $\psi = 1$ (always accept) whenever the right-hand side of (3) is less than or equal to one, or equivalently

$$\gamma(g) \;\geq\; \frac{p}{p + (1-a)(v-p)}. \tag{6}$$

This inequality places only a lower bound on the fraction of good borrowers needed for unconditional acceptance; there is no upper bound, so in the corner case beliefs can improve all the way to $\gamma(g) = 1$.

It turns out that whether $\psi = 1$ or $\psi > 1$ defines two distinct regimes of optimal contracts. Proposition 1 shows that every optimal contract is either separating with $\psi = 1$ or pooling with $\psi > 1$ (unless $V = 0$). Pooling is sustainable only when acceptance is selective ($\psi > 1$). When $\psi = 1$, a lender can profitably deviate to an otherwise identical separating contract that attracts only good borrowers, causing any pooling contract to unravel (Guerrieri, Shimer, and Wright, 2010). When $\psi > 1$, however, such deviations are not feasible: if only good borrowers applied, the deviating lender would have no incentive to screen, inducing bad borrowers to return. Since pooling with $\psi = 1$ is never optimal (except in the trivial case $V = 0$), we use the term *pooling contracts* to refer specifically to contracts with a non-degenerate applicant pool and $\psi > 1$.

Proposition 1. *When $V > 0$, an optimal contract takes one of two forms:*

(i) Separating contract: (p, γ, θ), *where* $\gamma(g) = 1$ *and* (p, θ) *solves*

$$\begin{aligned} V^S = \max_{p,\theta} \quad & m(\theta)(v-p) \\ s.t. \quad & n(\theta)(p-c) = k(g), \\ & n(\theta)p \leq k(b). \end{aligned} \tag{7}$$

(ii) Pooling contract: (p, γ, θ), *where*

$$\gamma(g) = \Gamma(p, \psi), \quad p < v, \quad \psi > 1,$$

and (p, θ, ψ) *solves*

$$V^P = \max_{p,\theta,\psi} \quad m(\theta)\Big[\Gamma(p,\psi)\psi^{-\frac{1-a}{a}}(v-p) - (1-\Gamma(p,\psi))\psi^{-\frac{1}{a}}p\Big] \tag{8}$$

$$s.t. \quad n(\theta)\psi^{-\frac{1-a}{a}}(p-c) = k(g),$$

$$n(\theta)\psi^{-\frac{1}{a}}p = k(b).$$

Finally, equilibrium lender profit $V = \max\{V^S, V^P, 0\}$.

The equilibrium analysis proceeds by solving for the optimal contract in each regime and then comparing lender profit under an *optimal separating contract* (maximizing profit among separating contracts) and an optimal pooling contract (maximizing profit among pooling contracts with $\psi > 1$).

3.1 Optimal Separating Contracts

We begin by analyzing optimal separating contracts, which themselves fall into two sub-regimes: unconstrained (first best) and constrained. The unconstrained separating contract corresponds to the solution of a relaxed optimal contract problem, where the incentive compatibility constraint that the bad type does not want to come to the contract is dropped. We then characterize the optimal incentive-compatible separating contract when that constraint binds.

Unconstrained Optimal Separating Contract Proposition 2 analyzes the first-best contract problem, where only the participation constraint is imposed and incentive compatibility is ignored. Since bad borrowers generate no gains from trade, the first-best contract targets only good borrowers ($\gamma(g) = 1$). We refer to the solution as the *unconstrained optimal separating contract*. The queue length in the unconstrained optimal separating contract maximizes total gains from trade, $m(\theta)(v-c)$, net of participation costs, $\theta k(g)$.

Proposition 2. *The solution to the first-best contract problem*

$$V^S = \max_{p,\theta} \quad m(\theta)\,(v-p),$$

$$s.t. \quad n(\theta)\,(p-c) = k(g),$$

is

$$\theta^* = \arg\max_{\theta} \{\, m(\theta)(v-c) - \theta k(g) \,\}, \qquad p^* = c + \frac{k(g)}{n(\theta^*)}.$$

The resulting contract is incentive compatible (i.e., (p^*, θ^*) *satisfies the inequality constraint in* *the optimal separating problem* (7)*) if and only if*

$$k(b) \;\geq\; k_0 \equiv k(g) + n(\theta^*)\, c.$$

Constrained Optimal Separating Contract Incentive compatibility of a contract requires that the total cost for bad borrowers, $k(b)$, weakly exceeds the combined participation and expected production cost of good borrowers. For the first best contract, the requirement is $k(b) \geq k_0$. If instead $k(b) < k_0$, the first-best contract would yield strictly positive profits for bad borrowers, inducing them to mimic good borrowers. To deter such deviations, the lender must distort the contract by reducing the meeting probability of borrowers, which effectively lowers the expected production cost for good borrowers. This adjustment equates the total cost for bad borrowers with the combined participation and expected production cost of good borrowers, thereby restoring incentive compatibility. The resulting contract is the constrained optimal separating contract described in Proposition 3.

Proposition 3. *Let* $\bar{k} = \frac{v}{v-c}k(g)$*. If* $k(b) \in (\bar{k}, k_0)$*, the optimal separating contract solving* (7) *is given by*

$$\theta^S = n^{-1}\left(\frac{k(b) - k(g)}{c}\right), \qquad p^S = \frac{k(b)}{k(b) - k(g)}c.$$

If $k(b) \leq \bar{k}$*, every eligible separating contract yields non-positive lender profit.*

Together, Proposition 2 and Proposition 3 characterize the lender-optimal separating contracts depending on whether the incentive compatibility constraint binds. In all separating contracts, the lender accepts trades unconditionally (i.e., $\psi = 1$), and the contract structure parallels those studied in Rothschild and Stiglitz (1976) and Guerrieri, Shimer, and Wright (2010).

3.2 Optimal Pooling Contracts

We now turn to pooling contracts where lenders attract both good and bad borrowers and use data-based screening before making a loan. Proposition 4 below discusses the existence, uniqueness, and structure of an optimal pooling contract. Intuitively, increasing selectiveness allows data-based screening to substitute for screening through higher prices (and thus longer queues), because both instruments disproportionately burden bad borrowers. Since price falls with selectiveness, the optimal-acceptance condition requires applicant quality to decline as selectiveness rises. These forces generate the central tradeoff: greater selectiveness permits a lower price but requires a worse applicant pool and lowers the lender's trading probability, both directly (via a stricter acceptance rule) and indirectly (via a shorter queue). The optimal pooling contract balances these effects.

Proposition 4. *Suppose $k(b) \in (k_2, k_0)$, where $k_2 = \bar{k}/\psi_{\max}$ and $\psi_{\max} > 1$ satisfies $k(g) = U(v, \psi_{\max})$. Then the reduced optimal pooling problem (11) defined in Lemma 2 admits a unique maximizer.*

If the maximizer is $\psi = 1$, all pooling contracts are dominated by the constrained separating contract or by non-participation. If instead the maximizer satisfies $\psi > 1$, the optimal pooling contract is given by

$$p^P = P(\psi), \qquad \theta^P = n^{-1}\big(\tfrac{k(g)}{U(p^P,\psi)}\big), \qquad \gamma^P(g) = \Gamma(p^P, \psi),$$

and $(p^P, \gamma^P, \theta^P)$ yields non-negative lender profit. $P(\psi)$ and $U(p, \psi)$ are the closed–form functions defined in Lemma 1.

Lemma 1. *Each eligible pooling contract can be indexed by the selectiveness level ψ via*

$$p = P(\psi) = \frac{\psi}{\psi - k(g)/k(b)}\, c, \tag{9}$$

$$\theta = n^{-1}\Big(\tfrac{k(g)}{U(P(\psi),\psi)}\Big), \tag{10}$$

$$\gamma(g) = \Gamma(P(\psi), \psi),$$

where

$$U(p, \psi) = \psi^{-\frac{1-a}{a}}\big(p - c\big)$$

is the matching surplus of good borrowers.

Because the participation constraints tie p and θ to the selectiveness level ψ, each eligible pooling contract is fully indexed by ψ (Lemma 1). Given Lemma 1, the optimal pooling problem (8) reduces to a single-variable maximization over ψ, as shown in Lemma 2.

Lemma 2. *The problem of the optimal pooling contract (8) simplifies to*

$$\max_{\psi}\ \hat{V}^P\big(P(\psi), \psi\big), \tag{11}$$

$$s.t.\ \ k(g) \le U\big(P(\psi), \psi\big), \tag{12}$$

$$\psi \ge \max\{1, \psi_{\min}\},$$

where

$$\hat{V}^P(p, \psi) = a\, m\Big(n^{-1}\big(\tfrac{k(g)}{U(p,\psi)}\big)\Big)\Gamma(p, \psi)\, \psi^{-\frac{1-a}{a}}(v - p),$$

is the lender's expected profit and

$$\psi_{\min} = \frac{v}{v - c}\,\frac{k(g)}{k(b)}$$

is the minimum selectiveness level consistent with $P(\psi) \leq v$.

Observe that

$$m\Big(n^{-1}\big(\tfrac{k(g)}{U(p,\psi)}\big)\Big)\,\Gamma(p,\psi)\,\psi^{-\frac{1-a}{a}}\,(v-p)$$

represents the expected gain the lender obtains when trading with good borrowers. The lender's overall profit is simply a times this expected gain because, under our information structure, the informativeness parameter a determines the extent of *cross-subsidization* in pooling contracts: the expected loss from trading with bad borrowers is exactly $(1-a)$ times the gain from good borrowers.

We next consider two commonly assumed matching functions for which the lender's optimal selectiveness level ψ can be characterized in closed form.

Example 1 Consider the Leontief matching function $m(\theta) = \min\{\theta, 1\}$. The optimal pooling contract cannot feature $\theta < 1$: if it did, the lender could offer an otherwise identical contract with $\theta = 1$, leaving borrowers indifferent while raising their own meeting probability and hence profit. We therefore restrict attention to $\theta \geq 1$. In this case, the derivative of the log profit function with respect to ψ is

$$\frac{-D_1 D_2\left(\psi - (1-a)\,\frac{k(g)}{k(b)}\right) \;+\; a\psi\left(\psi - \frac{k(g)}{k(b)}\right)\,\frac{c}{v-c}}{a\psi\left(\psi - \frac{k(g)}{k(b)}\right)D_1 D_2},$$

where $D_1 = \psi - \psi_{\min}$, $\quad D_2 = (1-a)(\psi - \psi_{\min}) + \frac{c}{v-c}$.

The numerator is a cubic polynomial in ψ with a negative leading coefficient. It evaluates positively at $\psi_{\min}$ and negatively at $(1-a)\,\frac{k(g)}{k(b)}$. Hence it admits three real roots: one below $(1-a)\frac{k(g)}{k(b)}$, one above $\psi_{\min}$, and one in between. For $\psi > \psi_{\min}$, the numerator is strictly positive until the largest root, denoted ψ_0^*, and strictly negative thereafter. Since the denominator is strictly positive on this domain, lender profit is maximized at $\max\big\{\,1,\ \min\{\psi_0^*, \bar{\psi}\}\,\big\}$, where $\bar{\psi}$ is the upper bound imposed by the participation constraint (12).

Example 2 Consider the Cobb-Douglas matching function:

$$m(\theta) = \min\left\{\theta,\ A^{\alpha}\theta^{\alpha},\ 1\right\},$$

with $0 < A, \alpha < 1$. This formulation captures linear matching at low θ, Cobb-Douglas behavior in the intermediate range, and saturation at high θ.

Define the bunching threshold $\hat{\psi}$ as the solution to

$$k(g) = A\,U(P(\psi), \psi),$$

at which implied tightness reaches $\hat{\theta} = 1/A$ and the matching elasticity falls from α to 0.

We begin by abstracting from the upper and lower bounds on ψ. When $\psi < \hat{\psi}$, the implied market tightness satisfies $\theta^P < 1/A$, placing the matching function in the saturation region. The first-order condition for the log profit function then coincides with Example 1, and lender profit is maximized at $\min\{\psi^*, \hat{\psi}\}$.

When $\theta^P > 1/A$ or $\psi > \hat{\psi}$, the matching function is in the Cobb–Douglas region. In this case, the first-order condition is

$$\frac{-D_1 D_2\Big(\psi - (1-a)\frac{k(g)}{k(b)}\Big) \;+\; (1-\alpha)a\psi\Big(\psi - \frac{k(g)}{k(b)}\Big)\frac{c}{v-c}}{(1-\alpha)a\psi\Big(\psi - \frac{k(g)}{k(b)}\Big)D_1 D_2},$$

and lender profit is maximized at $\max\{\psi^*_\alpha, \hat{\psi}\}$, where ψ^*_α denotes the largest root of the numerator above.

By monotone comparative statics, we know that $\psi^*_0 > \psi^*_\alpha$. Combining both regions, the overall maximizer of lender profit is therefore the median of the three values $\{\psi^*_0, \psi^*_\alpha, \hat{\psi}\}$. Once we impose the upper and lower bounds on ψ, the final solution $\max\{1, \min\{\psi^*, \bar{\psi}\}\}$, where ψ^* is the median of $\{\psi^*_0, \psi^*_\alpha, \hat{\psi}\}$.

Notably, ψ^*_α depends only on the ratio $\frac{k(g)}{k(b)}$, rather than on $k(g)$ or $k(b)$ individually. Thus, when the equilibrium queue length lies in the Cobb–Douglas region of the matching function, the optimal ψ is pinned down entirely by this ratio. In the calibration of Section 4, we exploit this property: we first assume the economy operates in the Cobb–Douglas region and calibrate the model parameters accordingly, and then confirm that the implied tightness indeed falls within that region.

3.3 Equilibrium

In our model, equilibrium analysis hinges on comparing lender profits under optimal separating versus optimal pooling contracts. If the optimal unconstrained optimal separating contract is incentive compatible, it achieves the first-best outcome and dominates all pooling contracts. Thus, the relevant comparison arises only when the incentive compatibility constraint binds. Lemma 3 formalizes this comparison by characterizing how lender profit under the optimal constrained optimal separating and optimal pooling contracts responds to changes in $k(b)$.

Lemma 3. *For all $k(b) \in (\bar{k}, k_0)$, the elasticity of profit with respect to $k(b)$ is smaller under pooling than under separating:*

$$\frac{\partial \log V^P}{\partial \log k(b)} < \frac{\partial \log V^S}{\partial \log k(b)}.$$

The inequality in Lemma 3 arises from two central sources. First, the price under the constrained optimal separating contract p^S is more sensitive to changes in $k(b)$ than the price under the pooling contract p^P when $\psi > 1$. This implies that the marginal effect of $k(b)$ on price is greater in the separating contract.

Second, lender profit under the pooling contract is less negatively affected by an increase in the posted price than under the separating contract. This difference in elasticity reflects both a direct effect and indirect effects mediated by changes in equilibrium queue length and the composition of applicants. Because the pooling price p^P is lower than the separating price p^S, the lender enjoys a greater gain from trade under pooling, and marginal increases in p^P erode this gain more slowly than equivalent increases in p^S would in the separating contract.

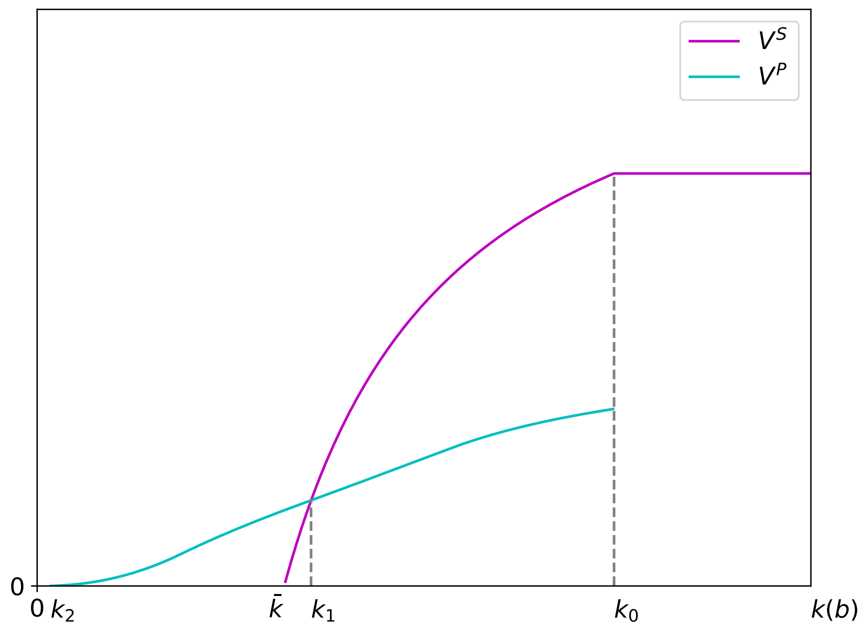
In addition, the lower price in the pooling contract implies that good borrowers' gain from trade is smaller than under separation. Consequently, a marginal increase in price leads to a larger proportional increase in borrowers' gain under pooling. Through endogenous adjustment of queue length, this increase in borrowers' gain positively affects lender meeting probability. Moreover, the elasticity of lender meeting probability with respect to borrowers' gain is $\frac{\epsilon(\theta^P)}{1-\epsilon(\theta^P)}$ in the pooling regime and $\frac{\epsilon(\theta^S)}{1-\epsilon(\theta^S)}$ in the separating regime. Since the queue length is shorter under pooling, and the elasticity $\epsilon(\theta)$ is assumed to be weakly decreasing in θ, the responsiveness of lender meeting probability to borrowers' gain is greater under pooling. This further dampens the negative effect of price increases on lender profit.

Finally, under pooling, the applicant composition adjusts with the price. A higher price raises the share of good applicants, $\gamma(p^P, \psi)$, which mitigates the negative effect of higher prices on lender profit. Together, these forces make lender profit under pooling less sensitive to price, strengthening the relative appeal of pooling when $k(b)$ falls and bad borrowers become harder to deter.

These considerations imply that lender profit under the optimal pooling contract increases more slowly with $k(b)$ than under the separating contract. Figure Figure 2 illustrates this point by plotting lender profits under the unconstrained and constrained optimal separating contracts, V^* and V^S, together with the optimal pooling contract with $\psi > 1$, V^P, as functions of $k(b)$ while holding other parameters fixed. At k_0, the optimal separating contract achieves the first-best outcome and dominates the optimal pooling contract. At $\bar{k}$, the optimal separating contract yields zero profit and is dominated by the optimal pooling contract. The profit functions intersect exactly once at k_1, where lender profits under the two contracts are equal.

For $k(b) > k_1$, the optimal separating contract maximizes lender profit and is implemented

Figure 2: The Lender's Profit in Optimal Separating and Pooling Contracts



Notes: In this figure, we vary $k(b)$ while holding all other parameters constant. The magenta line shows lender profit under the unconstrained optimal separating contract (V^*), the blue curve shows profit under the constrained optimal separating contract (V^S), and the cyan curve shows profit under the optimal pooling contract with $\psi > 1$ (V^P). The threshold k_0 marks the smallest value of $k(b)$ for which the unconstrained separating contract remains incentive compatible. At k_1, the constrained separating and pooling contracts deliver the same profit. $\bar{k}$ denotes the lowest value of $k(b)$ for which the constrained separating contract yields non-negative profit, while k_2 is the analogous threshold for the pooling contract.

in equilibrium. When $k(b) \in (k_2, k_1)$, optimal pooling contracts deliver strictly higher lender profit and become the equilibrium contracts. However, for $k(b) < k_2$, even pooling contracts fail to make the lender profitable, and the equilibrium collapses to no trade.

Proposition 5. *An equilibrium exists and is payoff-unique. Holding all other parameters fixed and varying $k(b)$, there exist thresholds*

$$0 < k_2 < k_1 < k_0$$

that characterize the equilibrium contract posted by the lender:

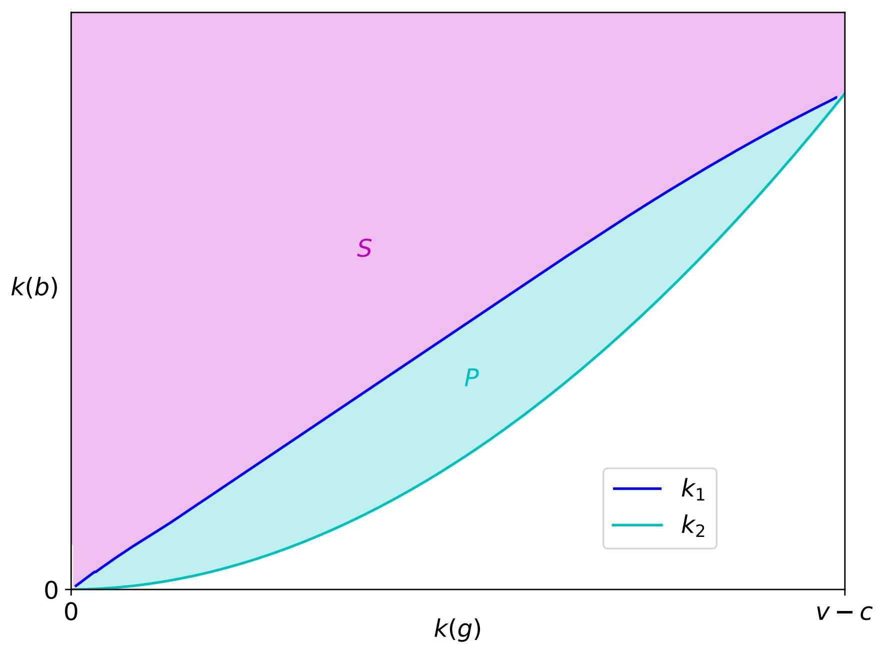
- $k(b) > k_1$*: Separating contract.*
- $k(b) \in (k_2, k_1)$*: Pooling contracts with selective acceptance.*
- $k(b) \in (0, k_2)$*: No trade.*

Proposition 5 follows directly from the preceding comparison. As illustrated in Figure 3, fixing other parameters, the equilibrium outcome depends on $k(b)$, which determines the ease of deterring bad borrowers from applying. When $k(b)$ is high, screening with price alone is optimal, resulting in the optimal separating contract. As $k(b)$ decreases beyond k_1, the separating price becomes undesirably high. In this range, it is more cost-effective for the lender to start to screen with data and adopt selective acceptance. Consequently, optimal pooling contracts emerge in equilibrium. However, if $k(b)$ decreases further and crosses the final threshold k_2, even pooling contracts are no longer viable, and the equilibrium collapses into a no-trade outcome.

In summary, the model generates a rich set of equilibrium regimes. As $k(b)$ decreases, the equilibrium undergoes a sequence of transitions: from separating to pooling with selective acceptance, and ultimately to autarky. These regime shifts reflect the changing tradeoffs between screening with prices and screening with data, and how the optimal contract adjusts as it becomes increasingly difficult to deter bad borrowers.

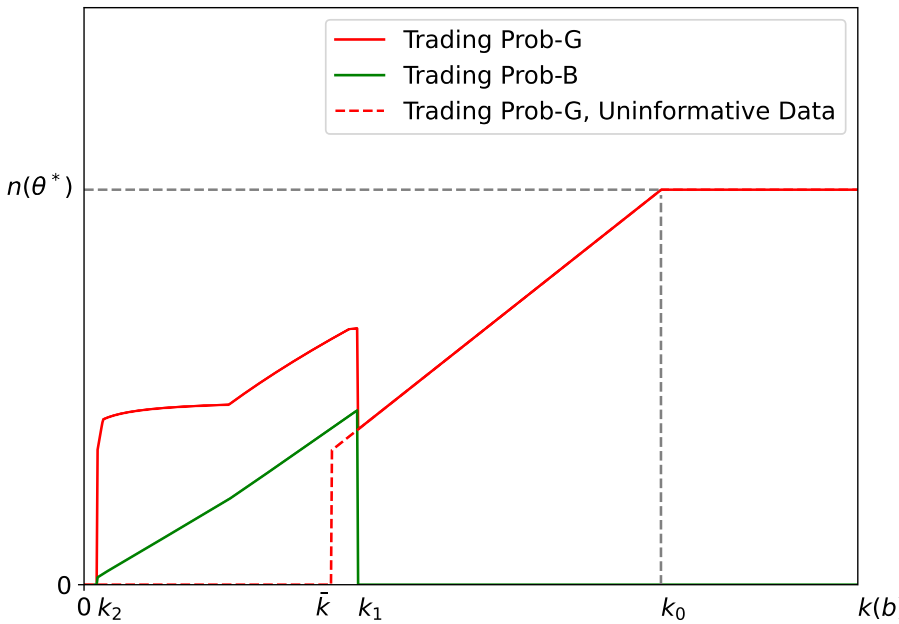
As the equilibrium transitions from separating to pooling, or from pooling to autarky, the economy undergoes sharp shifts in trading patterns, as illustrated in Figure 4 and Figure 5. Average selling probabilities by borrower type exhibit discrete jumps at the thresholds k_1 and k_2.[11] These discontinuities imply that in our model, market liquidity can be fragile: small changes in borrower participation costs may lead to abrupt shifts in contract form or even episodes of complete market freeze.

Figure 3: Equilibrium Regimes



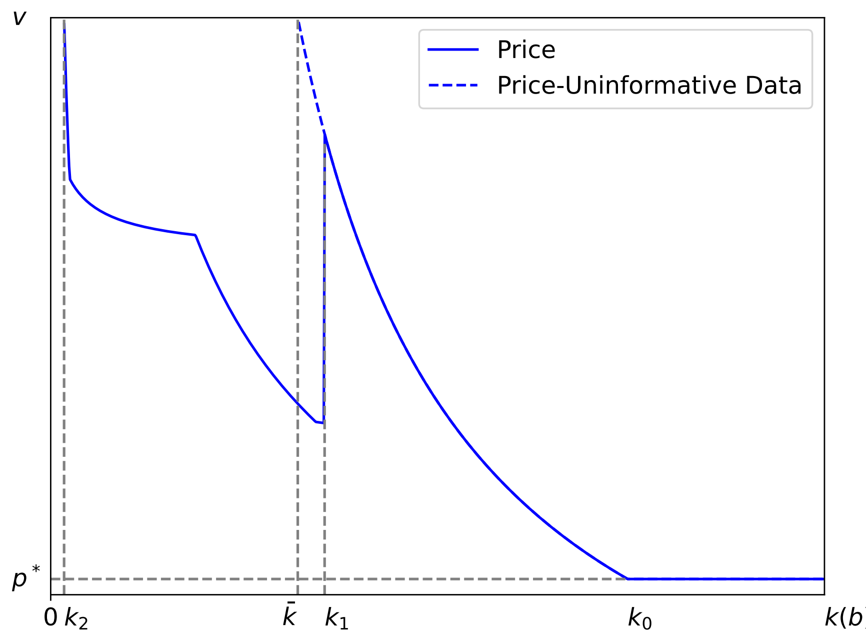
Notes: The figure illustrates the equilibrium regimes when $k(g) < v - c$. When $k(g) > v - c$, the gains from trade between good borrowers and the lender are insufficient to cover the participation cost of good borrowers, so the equilibrium collapses to autarky. The magenta shaded region ($k(b) > k_1$) corresponds to the regime of optimal separating contracts and the cyan region ($k(b) \in (k_2, k_1)$) to optimal pooling contracts with selective acceptance, and the unshaded region to no trade. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871.

Figure 4: Equilibrium Borrower Trading Probability



Notes: The red solid curve shows the overall trading probability (meeting probability × acceptance probability) for good borrowers in the equilibrium, while the green solid curve shows it for bad borrowers. Trading probabilities exhibit discrete jumps at k_1 and k_2. For comparison, the red dashed curve represents the trading probability for good borrowers in the equilibrium with uninformative data ($a = 0$); the corresponding probability for bad borrowers is always zero and thus omitted. The vertical line segments at k_1, $\bar{k}$, and k_2 indicate equilibrium multiplicity, where the lender is indifferent between two contracts and any convex combination of them constitutes an equilibrium. The kinks in the trading probability naturally arise from kinks in the bounded Cobb-Douglas matching function. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871 for the solid curves.

Figure 5: Equilibrium Price



Notes: The solid curve shows the equilibrium price, while the dashed curve provides the corresponding price under uninformative data ($a = 0$). The vertical line segment at k_1 indicates equilibrium multiplicity, where the lender is indifferent between the optimal constrained separating contract and the optimal pooling contract and any convex combination of them constitutes an equilibrium. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871 for the solid curve.

3.4 Limit Cases: Perfectly Informative Data ($a = 1$) or Uninformative Data ($a = 0$)

We begin with perfectly informative data ($a = 1$). In this case, F_g collapses to a mass point at $z = 1$. There is no quantity–quality tradeoff: accepting only when $z = 1$ ensures all good borrowers are accepted with probability one, while bad borrowers are almost surely rejected. Thus, selectivity eliminates bad borrowers without excluding good ones. Information frictions disappear, and the first-best outcome is attained through a screening-with-data contract that is isomorphic to the unconstrained optimal separating contract, except that the lender accepts only when $z = 1$.

Turning to uninformative data ($a = 0$), we have $F_g = F_b$, so the lender cannot screen with data and $\psi \equiv 1$. Equilibrium must therefore be separating, as in Guerrieri, Shimer, and Wright (2010). Proposition 6 characterizes this case. As illustrated in Figure 6, when $k(b)$ is low, the equilibrium features the optimal separating contract. If $k(b)$ rises beyond $\bar{k}$, the separating price becomes too high to sustain trade.

Proposition 6. *Assume data is uninformative ($a = 0$). An equilibrium exists and is payoff-unique. Holding all other parameters fixed and varying $k(b)$, there exist thresholds*

$$0 < \bar{k} < k_0,$$

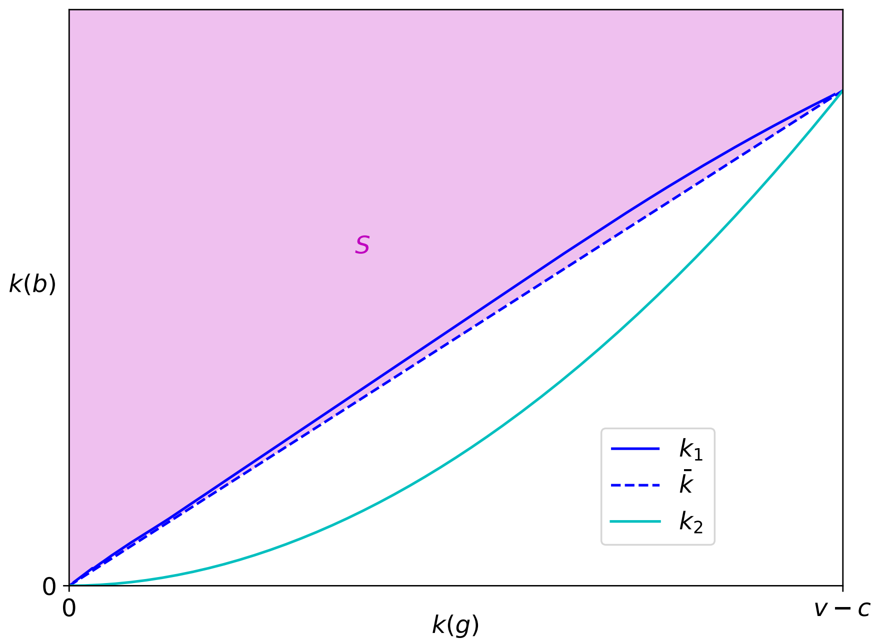
that characterize the equilibrium contract posted by the lender:

- $k(b) > k_0$*: Unconstrained optimal separating contract.*
- $k(b) \in (\bar{k}, k_0)$*: Constrained optimal separating contract.*
- $k(b) \in (0, \bar{k})$*: No trade.*

Figure 4 and Figure 5 compare equilibrium outcomes under informative and uninformative data. When $k(b) > k_1$, the two equilibria coincide: both feature a separating contract and yield identical outcomes. Similarly, for $k(b) < k_2$, both settings result in autarky with no trade. The key differences arise in the intermediate range. For $k(b) \in (\bar{k}, k_1)$, both equilibria support trade, but their structure diverges: the informative-data equilibrium is pooling, offering

[11] At k_1, the costs of screening with price and with data are equal, giving rise to a continuum of equilibria that can be represented as convex combinations of the separating and pooling contracts. Similarly, equilibrium multiplicity arises at k_2.

Figure 6: Equilibrium Regimes With Uninformative Data



Notes: The plot depicts the equilibrium regimes under uninformative data ($a = 0$) when $k(g) < v - c$. When $k(g) > v - c$, the gains from trade between good borrowers and the lender are insufficient to cover the participation cost of good borrowers, so the equilibrium collapses to autarky. The magenta shaded region ($k(b) > \bar{k}$) corresponds to the regime of optimal separating contracts and the unshaded region to no trade. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871.

a lower price and higher trading probabilities for both borrower types, while the uninformative-data equilibrium remains separating, with a higher price and a lower trading probability for good borrowers. When $k(b) \in (k_2, \bar{k})$, trade survives only in the informative-data setting; the uninformative-data equilibrium collapses into autarky.

3.5 Extension: Competitive Lenders and Lender Heterogeneity

In the baseline model, we assume a single lender and define optimal acceptance, the set of eligible contracts and the optimal contract for that lender. The framework extends naturally to an environment with many competitive lenders, possibly heterogeneous, as long as lender types are common knowledge. Let t denote a lender type and T the set of all types, capturing heterogeneity in data informativeness a_t, valuation g_t, and search technologies m_t and n_t. An equilibrium requires that, for each lender type $t \in T$, both optimal acceptance and optimal contract posting conditions are satisfied. As a result, each lender type has its own optimal acceptance, set of eligible contracts, and optimal contract.

In the equilibrium with heterogeneous competitive lenders, each lender type designs its own optimal contract, subject to lender-specific eligibility constraints that depend solely on borrower market utilities. With free entry on the borrower side, borrower market utilities are pinned down by participation costs and are therefore invariant to the distribution of lender types. As a result, an economy with heterogeneous lenders is isomorphic to a collection of single-lender economies, each corresponding to a specific lender type. In Section 4, we calibrate the extended model and examine how changes in lender informativeness, search technology, and discount rates affect the lending contracts.

3.6 Discussion: Free Entry versus Fixed Supply of Borrowers

Our baseline model assumes free entry on the borrower side: market utilities are fixed at $k(g)$ and $k(b)$, while the number of participating borrowers adjusts endogenously. The framework can also accommodate an alternative environment in which the supplies of good and bad borrowers are fixed at $M(g)$ and $M(b)$, respectively, and borrower market utilities become endogenous. With a slight abuse of notation, we continue to let $k(g)$ and $k(b)$ denote these endogenous market utilities, which now depend on the distribution of lender types through the market-clearing conditions.

Let $\mu(t)$ denote the total capacity of type-t lenders, and let φ_t, supported on Y_t^*, denote the distribution of contracts posted by type-t lenders. Condition C3 requires that, for each lender type, the total mass of posted contracts does not exceed its capacity and, for each borrower type, the total number of applicants across all posted contracts does not exceed the fixed supply of that borrower type. These inequalities bind whenever the corresponding lender or borrower type earns strictly positive market utilities in equilibrium.

C3. Market Clearing:

$$\int_{Y_t^*} d\varphi_t(p,\gamma,\theta) \le \mu(t), \qquad \text{with equality if } V_t > 0,$$

$$\sum_{t\in T} \int_{Y_t^*} \theta\,\gamma(q)\, d\varphi_t(p,\gamma,\theta) \le M(q), \qquad \text{with equality if } k(q) > 0.$$

In Section 4, we maintain the baseline assumption of fixed borrower market utilities $k(g)$ and $k(b)$ for two reasons. First, potential borrowers realistically face an entry decision, and data suggest that the number of consumers searching for credit fluctuates over time. Second, small changes in lender composition, such as the initial arrival of Fintech lenders with limited capacity, are unlikely to substantially shift borrower market utilities. In such cases, counterfactual analyses that hold borrower utilities fixed are a reasonable approximation.

4 Application: Fintech Lending

In this section, we extend our baseline model with information heterogeneity across lenders to analyze Fintech lending. In credit markets, Fintech lenders typically have superior access to and use of alternative data compared to traditional banks. Di Maggio, Ratnadiwakara, and Carmichael (2022) show that Upstart, a leading personal loan Fintech, achieves an AUC of 66.1% by incorporating education, employment history, and device type used during application, compared with 60.4% for the Consumer Financial Protection Bureau's (CFPB) benchmark model based solely on traditional credit-report data. Since many banks still rely on models even less sophisticated than the CFPB benchmark, the informational advantage of data-rich Fintech lenders may be even greater. This advantage becomes especially pronounced when Fintech lenders possess proprietary customer data. Berg, Burg, Gombović, and Puri (2020) document that an e-commerce platform lender using digital footprints, including browsing behavior and device metadata, raises the AUC of default prediction to 73.6%. In decentralized finance (DeFi), RociFi, a protocol specializing in uncollateralized or under-collateralized lending, reports an AUC of 89% by leveraging extensive on-chain data associated with individual wallets.[12]

[12] See https://blog.roci.fi/rocifi-protocol-litapapar-12bd2c67a5ad.

4.1 Calibration

To calibrate the model, we focus on Upstart, since its AUC, interest rate, loan approval rate, and default rate are available from Di Maggio, Ratnadiwakara, and Carmichael (2022), and we discipline key parameters to match these moments.

Although Fintech lenders may face lower search frictions than traditional banks due to online or app-based borrower interactions (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019), empirical data on cross-lender differences in search technology are not available. We therefore assume that Upstart employs the same Cobb–Douglas matching function as traditional banks, with elasticity $\alpha = \frac{1}{2}$ and scale $A = 0.1369$, and calibrate the bank meeting probability to 1/4, following Petrosky-Nadeau and Wasmer (2013).

We back out the informativeness parameter a directly from the AUC. Upstart's model achieves an AUC of 66.1 percent, compared with 60.4 percent for the traditional benchmark (Di Maggio, Ratnadiwakara, and Carmichael, 2022). Using

$$\text{AUC} = \frac{1}{2-a},$$

we obtain $a = 0.4871$ for Upstart and $\underline{a} = 0.3444$ for traditional banks.

For the calibration, we define the good product as a fixed payment of one dollar each month for $N = 48$ months. We discipline the primitives $(v, c, \frac{k(g)}{k(b)})$ by matching three moments for Upstart: its 22 percent APR, 24.5 percent loan approval rate, and 4.1 percent default rate. Finally, we calibrate the participation cost, $k(b)$, so that traditional banks' meeting probability equals 0.25 (Petrosky-Nadeau and Wasmer, 2013).

Table 1 summarizes the calibrated parameter values and their source or target. A detailed explanation of how each parameter is derived from the data targets is provided in the Appendix.

	Description	Value	Source/Target
A	Matching Efficiency	0.1369	Petrosky-Nadeau and Wasmer (2013)
α	Matching Elasticity	0.5	Petrosky-Nadeau and Wasmer (2013)
a	Upstart Informativeness	0.4871	AUC of Upstart
$\underline{a}$	Bank Informativeness	0.3444	AUC of CFPB model
v	Lender Value (Good)	34.386	Interest, Approval and Default Rates of Upstart
c	Production Cost (Good)	23.560	Interest, Approval and Default Rates of Upstart
$k(g)$	Participation Cost (Good)	0.50264	Interest, Approval and Default Rates of Upstart
$k(b)$	Participation Cost (Bad)	0.56194	Meeting Probability of Traditional Banks

Table 1: Calibrated Parameters

We solve for the equilibrium of the calibrated model, with the resulting values of key equilibrium variables reported in the second column of Table 2.[13] In particular, under the calibrated parameters, the first-best contract implies a borrower meeting probability of 0.2738, while the incentive compatibility constraint limits this probability to at most 0.0025. Thus, the first-best outcome is not incentive compatible. Furthermore, implementing the constrained optimal separating contract would require a price of 223, which exceeds lenders' valuation of the good product. Lenders would therefore incur losses by offering such a contract. Consequently, no separating contract can exist in equilibrium, and the equilibrium outcome is pooling.

4.2 Effects of Information Friction

Generic Results A more selective acceptance rule lowers both the acceptance probability and the share of good borrowers in the applicant pool, imposing a cost on lenders. When data are more informative, this cost is smaller because increased selectivity has a weaker effect on acceptance rates and applicant quality. Hence, higher selectiveness becomes more attractive as data informativeness improves, which also allows lenders to offer a lower price while still attracting a mix of good and bad borrowers. Proposition 7 summarizes the result.

Proposition 7. *If (p, γ, θ) with $\psi > 1$ is the optimal pooling contract under data informativeness a, then there exists an optimal pooling contract $(\tilde{p}, \tilde{\gamma}, \tilde{\theta})$ under higher data informativeness $\tilde{a} > a$ such that $\tilde{\psi} \geq \psi, \tilde{p} \leq p$.*

Greater informativeness, however, does not necessarily lead to higher match quality. In pooling contracts, optimal acceptance requires that the break-even precision equal the lender's

[13] We back out a loan's interest rate (APY) by inverting the present value equation

$$p = \sum_{t=1}^{N} \frac{1}{(1 + \text{APY}/12)^t}.$$

The model's default rate follows directly as

$$\text{DR} = 1 - \hat{\gamma}(g) = \frac{\gamma(b)}{\gamma(g)\psi + \gamma(b)},$$

while the loan approval rate is the average of true and false positive rates weighted by applicant type share,

$$\text{LAR} = \gamma(g)\,\text{TPR} + \gamma(b)\text{FPR}.$$

Finally, the lender's internal rate of return is found by solving

$$p = \sum_{t=1}^{N} \frac{1 - \text{DR}}{(1 + \text{IRR}/12)^t},$$

so that each period's expected payment $(1 - \text{DR})$ exactly discounts to the upfront price p.

	Description	Traditional Banks ($\underline{a} = 0.3444$)	Upstart ($a = 0.4871$)	E-commerce Platform ($\overline{a} = 0.6413$)
ψ	Selectiveness	3.283	3.471	3.705
p	Price	32.383	31.740	31.059
θ	Queue Length	0.456	2.639	7.042
$\gamma(b)$	Applicant Share (bad)	0.117	0.129	0.125
$\gamma(g)$	Applicant Share (good)	0.883	0.871	0.875
$m(\theta)$	Lender Meeting Probability	0.250	0.601	0.982
$n(\theta)$	Borrower Meeting Probability	0.548	0.228	0.139
FPR	Acceptance Prob. (bad)	0.032	0.078	0.130
TPR	Acceptance Prob. (good)	0.104	0.270	0.481
$n(\theta)$FPR	Trading Prob. (bad)	0.017	0.018	0.018
$n(\theta)$TPR	Trading Prob. (good)	0.057	0.061	0.067
V^P	Lender Profit	0.016	0.182	0.882
AUC	Area Under the ROC Curve	60.4%	66.1%	68.3%
APY	Interest Rate	20.8%	22.0%	23.3%
LAR	Loan Approval Rate	9.6%	24.5%	43.7%
DR	Default Rate	3.9%	4.1%	3.7%
IRR	Internal Rate of Return	18.6%	19.6%	21.1%

Table 2: Cross-lender Comparison

profit margin (Equation (5)). Better data lowers the equilibrium price, which raises the profit margin and therefore increases the required $\bar{\gamma}(b)$. Under our information structure,

$$\frac{\gamma(b)}{\gamma(g)} = (1-a)\psi\,\frac{\bar{\gamma}(b)}{\bar{\gamma}(g)}, \qquad \frac{\hat{\gamma}(b)}{\hat{\gamma}(g)} = (1-a)\frac{\bar{\gamma}(b)}{\bar{\gamma}(g)}.$$

Since $\bar{\gamma}(b)$ decreases in a, the quality of applicants and the quality of accepted matches may either rise or fall with a.

Results from the Calibrated Model We then use the calibrated model for counterfactual exercises that vary lender informativeness to levels corresponding to traditional banks and to an e-commerce platform lender with access to digital footprints. For traditional banks, we again set $a = 0.3444$; the corresponding equilibrium is shown in the first column of Table 2. For the e-commerce platform, we set $a = 0.6413$, based on the AUC of 73.6% reported by Berg, Burg, Gombović, and Puri (2020); the resulting equilibrium is shown in the last column of Table 2.

Traditional banks operate with a less selective acceptance rule, but, due to their informational disadvantage, approve fewer borrowers. Despite higher meeting probabilities, borrowers who apply to banks face lower overall trading probabilities, combining matching and acceptance. Banks also have lower default rates but earn lower internal rates of return and substantially smaller profits. In contrast, Upstart's better data allow it to expand credit access more effectively and more profitably.

Raising informativeness from the level of Upstart to that of the e-commerce lender in Berg, Burg, Gombović, and Puri (2020) further increases approval rates, trading probabilities, and lender profitability. In contrast to the move from banks to Upstart, which increases default rates, the move from Upstart to the e-commerce platform lowers defaults.

The counterfactual results align with evidence showing that traditional credit models are far more restrictive in approving borrowers than Upstart's model (Di Maggio, Ratnadiwakara, and Carmichael, 2022), and that digital footprint data improve both approval rates and default performance (Berg, Burg, Gombović, and Puri, 2020).

Importantly, the counterfactual exercises highlight that our framework generates a non-monotonic relationship between data informativeness and the quality of accepted matches. This prediction is consistent with empirical evidence: even with access to better data, Fintech lenders do not always experience lower default rates. As Berg, Fuster, and Puri (2022) emphasize, empirical comparisons of Fintech and bank loan performance are mixed. In the U.S. mortgage market, Buchak, Matvos, Piskorski, and Seru (2018) find no performance differences, while Fuster, Plosser, Schnabl, and Vickery (2019) show that Fintech loans perform better in the FHA segment. By contrast, in the personal loan market, Di Maggio and Yao (2021) document higher delinquency rates for Fintech lenders.

The fact that Fintech lenders sometimes experience higher default rates despite having better data may reflect their expansion of credit access to lower-score, and thus less creditworthy, borrowers. For instance, Di Maggio, Ratnadiwakara, and Carmichael (2022) show that in the personal loan market, the leading Fintech lender, Upstart, concentrates lending in low-score segments, while in the mortgage market, Quicken Loans, another major Fintech player, also targets low-score borrowers more heavily than traditional banks.

4.3 Effects of Search Frictions

We analyze how search frictions influence the credit market. In particular, we focus on two commonly studied characteristics of the matching function: matching elasticity and search efficiency. We examine how changes in these characteristics affect the lender's optimal level of selectiveness ψ, and in turn, how they influence equilibrium outcomes.

Generic Results A reduction in search frictions, whether through lower matching elasticity or through greater search efficiency, induces more selective acceptance. This, in turn, leads to lower prices and a lower average quality of the applicant pool. These results are formally established in Proposition 8.

Proposition 8. *Consider the Cobb–Douglas matching function (Example 2)*

$$m(\theta) = \min\{\theta,\ A^{\alpha}\theta^{\alpha},\ 1\}.$$

Suppose $\tilde{\alpha} \leq \alpha$ *and* $\tilde{A} \geq A$. *If* (p, γ, θ) *with* $\psi > 1$ *is the optimal pooling contract under* (α, A)*, then there exists an optimal pooling contract* $(\tilde{p}, \tilde{\gamma}, \tilde{\theta})$ *under* $(\tilde{\alpha}, \tilde{A})$ *such that* $\tilde{\psi} \geq \psi, \tilde{p} \leq p, \tilde{\gamma}(g) \leq \gamma(g)$.

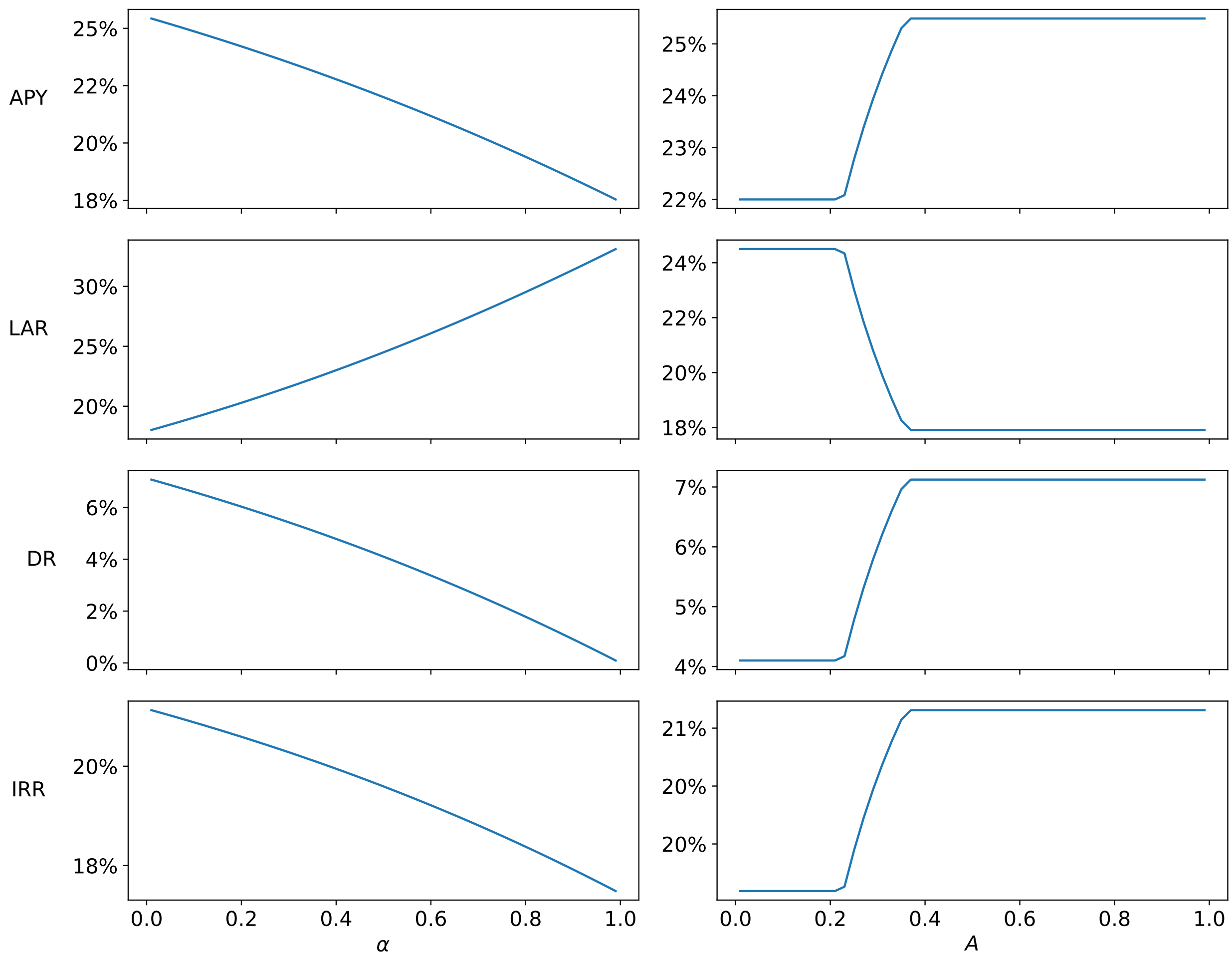
Intuitively, a more selective acceptance rule lowers the probability of acceptance and allows lenders to reduce the price while still attracting both good and bad borrowers. To offset the lower acceptance probability and price, lenders must raise the borrower meeting probability by shortening queues, which in turn reduces their own meeting probability. When matching elasticity is low, this reduction is smaller, making selectiveness more attractive.[14] Credibility of greater selectiveness at a lower price requires that the share of good borrowers in the applicant pool falls. Consequently, a lower matching elasticity raises optimal selectiveness, leading to a pooling contract with a lower price and worse average applicant quality. Higher search efficiency produces a similar effect.

Results from the Calibrated Model In the credit market, a reduction in search frictions, whether through lower matching elasticity or higher search efficiency, raises the loan APY, lowers the loan approval rate, increases the default rate, and enhances lender profitability as measured by the internal rate of return. As illustrated in Figure 7, decreasing the matching elasticity α from 0.5 to 0.4 raises the loan APY from 22.0% to 22.8%, reduces the loan approval rate from 24.5% to 23.0%, and increases the default rate from 4.1% to 4.8%. Lender profitability also rises modestly, with the internal rate of return increasing from 19.6% to 19.9%.

When search frictions decline, as reasoned earlier, lenders become more selective. In equilibrium, the applicant pool worsens, which tends to raise defaults, while stricter screening by lenders works in the opposite direction. On balance, the decline in pool quality dominates, so default rates rise. Because the pool is worse and lenders screen more aggressively, loan approval rates fall. Greater selectiveness also allows lenders to reduce the loan amount relative to a given payment stream, raising the loan APY. Finally, reduced search frictions increase lender profitability.

[14] With a Leontief matching function (Example 1), matching elasticity is zero whenever borrowers are rationed, so improving borrower meeting probability does not diminish lender meeting probability. As a result, lenders optimally choose more selective acceptance rules under Leontief than under alternative matching functions.

Figure 7: Effects of Search Frictions



Notes: This figure plots how matching elasticity α and search efficiency A affect loan APY, loan approval rate, default rate, and lenders' internal rate of return. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871.

4.4 Effects of Lender Discount Rate

We also study how variations in the lender's discount rate influence the credit market. The discount rate, denoted by ρ, determines the lender's valuation of loan payments as

$$v = \sum_{t=1}^{N} \frac{1}{(1+\rho/12)^t}.$$

In practice, ρ reflects both the lender's cost of capital, which incorporates regulatory constraints on leverage, and the operational cost associated with issuing and servicing loans.

Generic Results Intuitively, a lower lender valuation reduces the opportunity cost of rejecting trade, making lenders more selective. Greater selectiveness, in turn, allows lenders to offer a lower price. Proposition 9 formalizes this relationship.

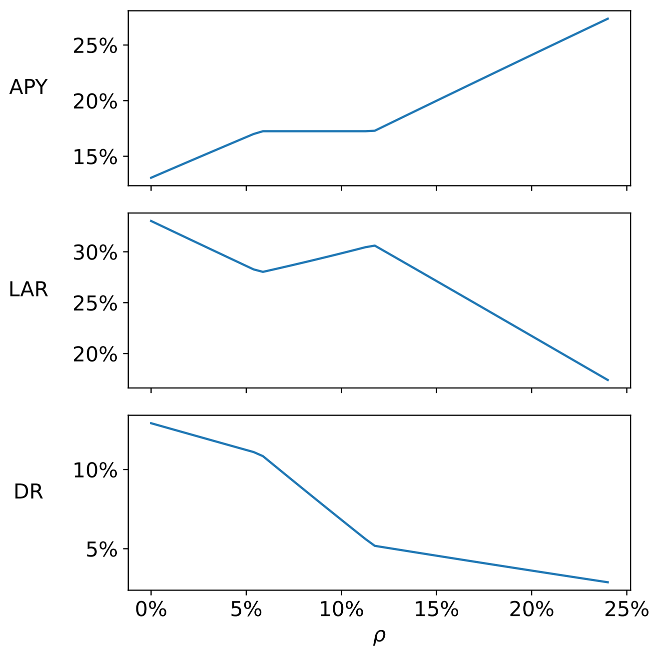
Proposition 9. *If (p, γ, θ) with $\psi > 1$ is the optimal pooling contract under lender valuation v, then there exists an optimal pooling contract $(\tilde{p}, \tilde{\gamma}, \tilde{\theta})$ under lower lender valuation $\tilde{v} \leq v$, such that $\tilde{\psi} \geq \psi, \tilde{p} \leq p$.*

Results from the Calibrated Model In the calibrated model, a higher lender discount rate raises loan APYs, reduces default rates, and has a non-monotonic effect on approval rates (Figure 8). Specifically, increasing ρ from 17.4% (baseline) to 20.9% (1.2× baseline) raises the APY from 22.0% to 24.8%, reduces defaults from 4.1% to 3.5%, and lowers approvals from 24.5% to 20.8%. Intuitively, a lower valuation of the loan payment stream makes lenders more selective by reducing the cost of selectivity. A more selective acceptance rule allows lenders to offer a smaller loan amount (price) for a given payment stream, thereby pushing up APYs. In equilibrium, greater selectiveness and a lower loan amount worsen applicant quality, while a lower lender valuation improves it. The latter effect dominates, so the overall applicant pool improves. With better applicants and stricter screening, defaults fall. Approval rates respond non-monotonically: a stronger applicant pool increases approvals for a given level of selectiveness, but higher selectiveness reduces approvals for a given pool. Our result is consistent with empirical studies such as Kovner and Van Tassel (2022), which find that increases in lenders' cost of capital are associated with tighter credit standards.

5 Conclusion

Our analysis shows that when lenders can condition trade on informative data, the nature of equilibrium screening in search markets changes fundamentally. When the participation cost

Figure 8: Effects of Search Frictions



Notes: This figure plots how lender discount rate ρ affects loan APY, loan approval rate and default rate. All other parameters are fixed at the levels reported in Table 1, with a set to 0.4871.

of bad borrowers is sufficiently high, lenders screen only through price, yielding a separating contract. As this cost falls, they switch to pooling contracts with selective acceptance. Even a small change in parameters can produce large, discontinuous changes in prices and trading probabilities. Information and search frictions jointly shape trading outcomes: reducing either information or search frictions lowers the effective cost of selectivity and leads lenders to become more selective in acceptance.

By embedding a one-parameter information structure that generates a smooth ROC curve, our model offers a tractable mapping from the empirical AUC to equilibrium contract outcomes. Calibrated to Fintech lenders and traditional banks, the model replicates key cross-sectional patterns: data-scarce traditional banks exhibit lower approval rates and earn slimmer profits. In contrast, data-rich Fintech lenders approve a larger fraction of loans and earn higher profits, yet some display higher default rates than banks. Our results imply that elevated default rates among "data-rich" lenders can arise not from screening failures but from equilibrium selection into lower-quality applicant pools. Policymakers and practitioners should therefore account for this mechanism when designing technologies or regulations that affect data quality, in order to balance credit access with lender asset quality.

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A Calibration Details

Di Maggio, Ratnadiwakara, and Carmichael (2022) report that the default model developed by Upstart achieves an AUC of 66.1% while the traditional model only achieves an AUC of 60.4%. In our framework, the AUC is given by

$$\text{AUC} = \frac{1}{2-a},$$

which implies a data informativeness parameter of $a = 0.48714$ for Upstart and $\underline{a} = 0.34437$ for traditional banks.

We define the "good" product as a fixed payment of one unit each month for N = 48 months. Our model's contract price p corresponds to the present value of these payments discounted at APY/12:

$$p \;=\; \sum_{t=1}^{N} \frac{1}{(1+\text{APY}/12)^t}.$$

Calibrating to Upstart's terms with 22% APR yields

$$p = 31.740.$$

We calibrate Upstart's selectiveness ψ and lender value v using Upstart's observed default rate (DR = 4.1%) and loan approval rate (LAR = 24.5%). In our model, these quantities satisfy the following equilibrium relationships:

$$\frac{\text{DR}}{1-\text{DR}} = (1-a)\frac{v-p}{p},$$

$$(1-\text{DR})\text{LAR} = \psi^{-\frac{1-a}{a}} \frac{p}{p+(1-a)\psi(v-p)}.$$

Solving these equations yields $\psi = 3.4706$ and $v = 34.386$.

Suppose that the equilibrium queue length lies in the Cobb-Douglas region of the matching function. Imposing Upstart's first-order condition

$$\begin{aligned} 0 = \; & -\left(\psi - \frac{v\,k(g)}{(v-c)\,k(b)}\right)\left[(1-a)\left(\psi - \frac{v\,k(g)}{(v-c)\,k(b)}\right) + \frac{c}{v-c}\right]\left(\psi - (1-a)\frac{k(g)}{k(b)}\right) \\ & + \; (1-\alpha)a\psi\left(\psi - \frac{k(g)}{k(b)}\right)\frac{c}{v-c}. \end{aligned}$$

together with the pricing equation

$$p = \frac{\psi}{\psi - \frac{k(g)}{k(b)}} c$$

yields the production cost and participation cost ratio: $c = 23.55963, \frac{k(g)}{k(b)} = 0.89448$. We then apply the analogous first-order condition and pricing equation for traditional banks to solve for their equilibrium selectiveness and price, finding $\underline{\psi} = 3.2828, \underline{p} = 32.38306$.

Following Petrosky-Nadeau and Wasmer (2013), we set $\alpha = 0.5, A = 0.1369$ and calibrate the meeting probability for traditional banks to $m(\underline{\theta}) = 0.25$. These imply a queue length of $\underline{\theta} = 0.45654$, which yields a borrower-side meeting probability $n(\underline{\theta}) = 0.54760$. We can then compute the bad-type participation cost

$$k(b) = n(\underline{\theta})\, \underline{\psi}^{-\frac{1}{a}}\, \underline{p} = 0.56193,$$

and the good-type participation cost

$$k(g) = 0.50264.$$

B Proofs

Proposition 1

Proof. From C1 and C2, a contract (p, γ, θ) is optimal (i.e., $(p, \gamma, \theta) \in Y^*$) if it is part of a solution to

$$\begin{aligned} \max_{p,\gamma,\theta,\psi} \quad & m(\theta)\Big(\gamma(g)\psi^{-\frac{1-a}{a}}(v-p) - \gamma(b)\psi^{-\frac{1}{a}}p\Big) \\ \text{s.t.} \quad & n(\theta)u(p,\gamma) \leq k(g), \quad \text{with equality whenever } \gamma(q) > 0, \\ & \psi \in \arg\max_{\psi} \ \gamma(g)\psi^{-\frac{1-a}{a}}(v-p) - \gamma(b)\psi^{-\frac{1}{a}}p.\psi \in [1,\infty) \cup \{\infty\} \end{aligned}$$

Notice that when $V > 0$, any optimal contract must satisfy $\gamma(g) > 0$ and $p < v$. If $\gamma(g) = 0$ or $p > v$, then $\psi = \infty$ and lender profit is zero. The same outcome arises if $p = v$ with $\gamma(g) < 1$. If $p = v$ with $\gamma(g) = 1$, lenders are indifferent over ψ, but profit is still zero. All three cases contradict $V > 0$. Furthermore, the optimal contract cannot have $\Psi(p, \gamma) = \infty$, since this again implies zero lender profit, inconsistent with $V > 0$.

The optimization problem can be decomposed depending on whether the lender's optimal acceptance rule has a corner solution ($\psi = 1$) or an interior solution ($\psi > 1$).

Case 1: Corner solution, $\psi = 1$. The corresponding subproblem is

$$\begin{aligned}\max_{p,\gamma,\theta} \quad & m(\theta)\Big(\gamma(g)(v-p) - \gamma(b)p\Big) \\ \text{s.t.} \quad & n(\theta)(p - c(q)) \leq k(q), \quad \text{with equality whenever } \gamma(q) > 0, \\ & \psi = 1, \quad \gamma(g) \geq \frac{p}{p + (1-a)(v-p)}.\end{aligned}$$

If an optimal contract solves this subproblem, we argue that it must have $\gamma(g) = 1$. From earlier reasoning, any optimal contract requires $\gamma(g) > 0$, so the participation constraint for good borrowers binds. Suppose instead that $0 < \gamma(g) < 1$, so that some bad borrowers also apply. Consider the alternative contract (p, δ_g, θ), where δ_g is a shorthand for the degenerate distribution concentrated entirely on g. Optimal acceptance implies that $\Psi(p, \delta_g) = 1$, so the alternative contract remains eligible. Moreover, the lender's profit strictly increases due to the removal of bad borrowers. This contradicts the optimality of (p, γ, θ). Therefore, the optimal contract under $\psi = 1$ must satisfy $\gamma(g) = 1$, and the subproblem reduces to the first optimization problem in Proposition 1.

Case 2: Interior solution, $1 < \psi < \infty$. The corresponding subproblem is

$$\begin{aligned}\max_{p,\gamma,\theta,\psi} \quad & m(\theta)\Big(\gamma(g)\psi^{-\frac{1-a}{a}}(v-p) - \gamma(b)\psi^{-\frac{1}{a}}p\Big) \\ \text{s.t.} \quad & n(\theta)(p - c(q)) \leq k(q), \quad \text{with equality whenever } \gamma(q) > 0, \\ & \psi > 1, \quad \gamma(g) = \Gamma(p, \psi).\end{aligned}$$

If an optimal contract solves this subproblem, it must satisfy $0 < \gamma(g) < 1$. To see why, note that from the earlier reasoning, any optimal contract requires $\gamma(g) > 0$ and $p < v$. Since $\gamma(g) = \Gamma(p, \psi)$ with $1 < \psi < \infty$ and $p < v$, it follows that $\gamma(g) < 1$. Hence, the interior solution necessarily features a

□

Proposition 2

Proof. Optimality of $(p^*, \delta_g, \theta^*)$.

Consider the problem

$$V^* = \max_{\theta} \; m(\theta)\big(v - c\big) \; - \; \theta\, k(g).$$

If $k(g) \in \big(0, \, v - c\big)$, the derivative of the objective at $\theta = 0$ is positive, so $\theta^* > 0$ and $V^* > 0$. Moreover,

$$p^* \; = \; c \; + \; \frac{\theta^* k(g)}{m(\theta^*)} \; < \; v.$$

Hence $\psi(p^*, \delta_g) = 1$, and $(p^*, \delta_g, \theta^*)$ achieves lender profit V^*.

What remains to be shown is that the lender profit in the relaxed problem cannot exceed V^*. If $\gamma(g) = 0$, lender profit in the relaxed problem is non-positive. If $\gamma(g) > 0$, eligibility requires

$$n(\theta)\, u(g; p, \delta_g) \;=\; k(g).$$

Lenders' profit in the relaxed problem cannot exceed

$$\max_{p,\gamma,\theta} \quad m(\theta)\,(v - p), \tag{13}$$

$$\text{s.t.} \quad n(\theta)\Psi(p,\gamma)^{-\frac{1-a}{a}}(p - c) = k(g). \tag{14}$$

Solving for p in (14) yields

$$p \;=\; c \;+\; \frac{k(g)}{n(\theta)\,\Psi(p,\gamma)^{-\frac{1-a}{a}}}.$$

Substitute into (13):

$$\begin{aligned}
m(\theta)\,\Psi(p,\gamma)^{-\frac{1-a}{a}}(v - p) &= m(\theta)\Big(v - c - \frac{k(g)}{n(\theta)\,\Psi(p,\gamma)^{-\frac{1-a}{a}}}\Big) \\
&= m(\theta)\big(v - c\big) - m(\theta)\frac{k(g)}{n(\theta)\,\Psi(p,\gamma)^{-\frac{1-a}{a}}} \\
&= m(\theta)\big(v - c\big) - \theta\,\Psi(p,\gamma)^{\frac{1-a}{a}}\,k(g),
\end{aligned}$$

where in the last step we use that $\frac{m(\theta)}{n(\theta)} = \theta$. Notice that the expression above decreases in $\Psi(p,\gamma)$. Thus, lender profit in the relaxed problem cannot exceed

$$\max_{\theta}\; m(\theta)\big(v - c\big) \;-\; \theta\, k(g).$$

Incentive compatibility.

The incentive compatibility constraint for type b is

$$n(\theta^*)\, u\big(b; p^*, \delta_g\big) \;\leq\; k(b).$$

Observe that

$$n(\theta^*)\, u\big(b; p^*, \delta_g\big) \;=\; n(\theta^*)\, u\big(g; p^*, \delta_g\big) \;+\; n(\theta^*)\big[u\big(b; p^*, \delta_g\big) - u\big(g; p^*, \delta_g\big)\big]\,.$$

The first term equals $k(g)$ by the participation constraint of good borrowers. The second term simplifies to $n(\theta^*)\, c$ since $\psi(p^*, \delta_g) = 1$. Hence,

$$n(\theta^*)\, u\big(b; p^*, \delta_g\big) \;=\; k(g) \;+\; n(\theta^*)\, c.$$

Therefore, the incentive compatibility requires

$$k(b) \;\geq\; k(g) + n(\theta^*)\, c.$$

$\square$

Proposition 3

Proof. Since $k(b) > k_0$,

$$\frac{k(b) - k(g)}{c} < n(\theta^*) \leq 1,$$

hence θ^S is well-defined.

When $k(b) > \bar{k}$,

$$p^S = \frac{k(b)}{k(b) - k(g)} c < \frac{\bar{k}}{\bar{k} - k(g)} c = v,$$

so $\psi(p^S, \delta_g) = 1$ and $(p^S, \delta_g, \theta^S)$ attains $V^S > 0$.

It remains to show that no eligible separating contract can generate a lender profit that exceeds V^S when $k(b) > \bar{k}$. Consider an eligible separating contract (p, γ, θ). If $\gamma(g) = 0$ or $p \geq v$, lender profit is non-positive, so it cannot exceed V^S. In the remaining case where $\gamma(g) > 0$ and $p < v$, the contract must satisfy $\Psi(p, \gamma) = 1$ and $n(\theta)(p - c) = k(g)$. In this case, the problem of constrained optimal separating contract reduces to

$$\max_{p,\theta}\; m(\theta)\,(v - p) \quad \text{s.t.} \quad n(\theta)\,(p - c) = k(g), \quad n(\theta)\, p \leq k(b).$$

Solving $n(\theta)(p - c) = k(g)$ gives

$$p = c + \frac{k(g)}{n(\theta)},$$

so the problem becomes

$$\max_{\theta}\; m(\theta)\big(v - c\big) \;-\; \theta\, k(g) \quad \text{s.t.} \quad \theta \geq \theta^S.$$

Since $\theta \mapsto m(\theta)(v - c) - \theta\, k(g)$ is concave (by concavity of m) and $\theta^* < \theta^S$ under $k(b) > k_0$, the constrained maximum occurs at $\theta = \theta^S$. Therefore, the highest profit attainable is V^S achieved by $(p^S, \delta_g, \theta^S)$. Hence, no eligible separating contract can yield more than V^S.

For $k(b) \leq \bar{k}$, no eligible separating contract yields a positive lender profit. To see this, consider any such contract (p, γ, θ). If $\gamma(g) = 0$ or $p \geq v$, the lender's profit is non-positive. If instead $\gamma(g) > 0$ and $p < v$, the highest possible profit is V^S, which is negative when $k(b) < \bar{k}$. □

Lemma 1

Proof. The participation constraints for both borrower types uniquely pin down p and θ as functions of the selectiveness level ψ, yielding the expressions in (9) and (10). The expression for γ as a function of (p, ψ) follows directly from the optimal acceptance condition in (4). Since p itself is a function of ψ alone, it follows that every eligible pooling contract is fully characterized by the single parameter ψ.

□

Lemma 2

Proof. Substituting the expressions for γ in (4) and for θ in (10) into the lender's profit function in (8) yields the simplified profit $\hat{V}^P(p, \psi)$ as stated. Since p is itself a function of ψ alone, the optimal pooling problem reduces to a maximization over the single variable ψ. □

Proposition 4

Proof. We first show that k_2 is well-defined. Since $k(g) < v - c$, the equation $k(g) = U(v, \psi)$ defines

$$\psi_{\max} = [\frac{k(g)}{v-c}]^{-\frac{a}{1-a}} > 1.$$

Next, I show that the constraint set of (11) is non-empty. Note that $U(P(\psi), \psi)$ is strictly decreasing in ψ and converges to zero as $\psi \to \infty$. Therefore, the constraint set is non-empty as long as $U(P(\psi_{\min}), \psi_{\min}) \geq k(g)$ and $U(P(1), 1) \geq k(g)$. As $k(b) > k_2$, we have:

$$\psi_{\min} = \frac{v}{v-c}\frac{k(g)}{k(b)} = \frac{\bar{k}}{k(b)} < \frac{\bar{k}}{k_2} = \psi_{\max}.$$

Since U decreases in its second argument, it follows that

$$U(P(\psi_{\min}), \psi_{\min}) = U(v, \psi_{\min}) > U(v, \psi_{\max}) = k(g).$$

As $k(b) < k_0$, we have

$$U(P(1), 1) = \frac{1}{1 - k(g)/k(b)}c - c > \frac{1}{1 - k(g)/k_0}c - c = \frac{k(g)}{n(\theta^*)} > k(g).$$

Since the objective function is continuous in ψ on the non-empty feasible set, a maximizer exists. Uniqueness follows if

$$\log \hat{V}^P(P(\psi),\psi) = \log m\Big(n^{-1}\big(\tfrac{k(g)}{U(P(\psi),\psi)}\big)\Big) + \log\Big(\Gamma(P(\psi),\psi)\,\psi^{-\frac{1-a}{a}}\,(v-P(\psi))\Big)$$

is strictly quasiconcave in ψ. The first term, $\log m(\cdot)$, is strictly decreasing in ψ. We now analyze the derivative of the second term:

$$D_\psi \log\Big[\Gamma(P(\psi),\psi)\,\psi^{-\frac{1-a}{a}}\,(v-P(\psi))\Big] = \frac{-D_1 D_2(\psi-k(b)(1-a)) + (1-\epsilon)a\,\psi(\psi-k(b))(v-c)c}{(1-\epsilon)a\,\psi(\psi-k(b))\,D_1 D_2}.$$

The numerator is a cubic polynomial in ψ with a negative leading coefficient. It is negative at $\psi=(1-a)k(b)$ but positive at $\psi=\psi_{\min}$. Thus, for $\psi>\psi_{\min}$, the numerator is strictly positive up to some point and strictly negative after that point. Since the denominator is strictly positive for $\psi>\psi_{\min}$, the derivative is strictly positive up to some point and strictly negative after that point. Hence, the second term is strictly quasiconcave in ψ. Together with the monotonicity of the first term, this implies that $\log \hat{V}^P(P(\psi),\psi)$ is strictly quasiconcave in ψ and therefore admits a unique maximum.

If (p,γ,θ) is a pooling contract, the two participation constraints

$$k(g) = n(\theta)\psi^{-\frac{1-a}{a}}(p-c), \tag{15}$$
$$k(b) = n(\theta)\psi^{-\frac{1}{a}}p \tag{16}$$

pin down p and θ as functions of ψ. Solving (15)–(16) gives

$$p = P(\psi) = \frac{\psi}{\psi-k(b)}, c, \tag{17}$$
$$\theta = n^{-1}\Big(\tfrac{k(g)}{U(P(\psi),\psi)}\Big), \quad U(p,\psi) = \psi^{-\frac{1-a}{a}}(p-c). \tag{18}$$

If $\psi^* > 1$ maximizes the optimization problem, then the optimal pooling contract satisfies

$$p^P = P(\psi^*),\ \gamma^P(g) = \Gamma\big(P(\psi^*),\psi^*\big),\ \theta^P = \theta(\psi^*).$$

If instead $\psi^*=1$, then

$$V^P = a\,m\big(\theta^S\big)\,\Gamma\big(p^S,1\big)\,(v-p^S) \ \le\ \big[m\big(\theta^S\big)\,(v-p^S)\big]^+ = [V^S]^+,$$

so every pooling contract is dominated by either the constrained separating contract or by non-participation.

□

Lemma 3

Proof. The semi-elasticity of lender profit with respect to $k(b)$ under each contract is given by the following expressions:

$$\frac{d\log V^P}{d\log k(b)} = \left(\frac{\epsilon(\theta^P)}{1-\epsilon(\theta^P)}\frac{p^P}{p^P-c} - \frac{p^S}{v-p^P} + \frac{\Gamma_p(p^P,\psi)p^P}{\Gamma(p^P,\psi)}\right)\frac{d\log p^P}{d\log k(b)},$$

$$\frac{d\log V^S}{d\log k(b)} = \left(\frac{\epsilon(\theta^S)}{1-\epsilon(\theta^S)}\frac{p^S}{p^S-c} - \frac{p^S}{v-p^S}\right)\frac{d\log p^S}{d\log k(b)},$$

where the price under the pooling contract is $p^P = \frac{\psi}{\psi-\kappa}c$, while the price under the separating contract is $p^S = \frac{1}{1-\kappa}c$, with $\kappa = \frac{k(g)}{k(b)}$.

Differentiating both expressions with respect to $k(b)$, we obtain:

$$\frac{d\log p^P}{dk(b)} = -\frac{\kappa}{\psi-\kappa}, \quad \text{and} \quad \frac{d\log p^S}{d\log k(b)} = -\frac{\kappa}{1-\kappa}.$$

Since when $k(b) > \bar{k}$, we have $p^S < v$, it follows that $\kappa < 1 < \psi$. Hence,

$$0 > \frac{d\log p^P}{d\log k(b)} > \frac{d\log p^S}{d\log k(b)}.$$

Moreover, since $\psi > 1$ for the optimal pooling contract, we have $p^P < p^S$ and thus participation constraints require that $n(\theta^P) > n(\theta^S)$. Because $\epsilon(\theta)$ is weakly decreasing, it follows that $\epsilon(\theta^P) \geq \epsilon(\theta^S)$. In addition, $\frac{\Gamma_p(p^P,\psi)p^P}{\Gamma(p^P,\psi)}$ is strictly positive. Thus,

$$\frac{\epsilon(\theta^P)}{1-\epsilon(\theta^P)}\frac{p^P}{p^P-c} - \frac{p^P}{v-p^P} + \frac{\Gamma_p(p^P,\psi)p^P}{\Gamma(p^P,\psi)} > \frac{\epsilon(\theta^S)}{1-\epsilon(\theta^S)}\frac{p^S}{p^S-c} - \frac{p^S}{v-p^S}.$$

Since $\frac{\partial \log \hat{V}^P}{\partial \psi} < 0$ and $\frac{d\log p^P}{d\psi} < 0$, optimality requires that the left-hand side of the above inequality be strictly negative.

Putting both pieces together, we conclude that the elasticity of lender profit with respect to $k(b)$ is strictly greater under the pooling contract than under the separating contract. That is,

$$\frac{\partial \log V^P}{\partial \log k(b)} < \frac{\partial \log V^S}{\partial \log k(b)}.$$

□

Proposition 5

Proof. When $\psi > \psi_{\min} > \frac{k(g)}{k(b)}$, $U(P(\psi), \psi)$ is continuous in ψ, so we can choose ψ slightly above $\psi_{\min}$ such that $U(P(\psi), \psi) > k(g)$. Also, because $P(\psi)$ is decreasing in ψ, it follows that $P(\psi) < P(\psi_{\min}) = v$. Together, these conditions imply $V^P > 0$ for $k(b) \in (k_2, k_0)$.

Let k_1 denote the solution to the indifference condition $V^P(k_1) = V^S(k_1)$ within the interval $(\bar{k}, k_0)$. Lenders' profit under the pooling contract is strictly lower than under the first-best contract, since $a < 1$; hence $V^P(k_0) < V^* = V^S(k_0)$. At the other endpoint, $V^P(\bar{k}) > 0 = V^S(\bar{k})$. By Lemma 3, there exists a unique $k_1 \in (\bar{k}, k_0)$ satisfying $V^P(k_1) = V^S(k_1)$. Moreover, $V^P < V^S$ for $k(b) \in (k_1, k_0)$, and $V^P > V^S$ for $k(b) \in (\bar{k}, k_1)$.

We now construct the equilibrium. Define borrowers' utility u, lenders' matching surplus v, and selectiveness ψ as in condition C1, and define the set of eligible contracts Y as in condition C2. Then set:

$$V = \begin{cases} V^*, & k(b) \geq k_0, \\ V^S, & k(b) \in [k_1, k_0), \\ V^P, & k(b) \in [k_2, k_1), \\ 0, & k(b) < k_2, \end{cases} \qquad Y^* = \begin{cases} \{(p^*, \delta_g, \theta^*)\}, & k(b) \geq k_0, \\ \{(p^S, \delta_g, \theta^S)\}, & k(b) \in [k_1, k_0), \\ \{(p^P, \gamma^P, \theta^P)\}, & k(b) \in [k_2, k_1), \\ \emptyset, & k(b) < k_2. \end{cases}$$

Condition C1 holds by construction of u, v, and ψ. It remains to verify C2. This follows from Proposition 2 for $k(b) > k_0$, from $V^S \geq V^P > 0$ for $k(b) \in [k_1, k_0)$, and from $V^P \geq V^S \geq 0$ for $k(b) \in [\bar{k}, k_1)$. For $k(b) \in [k_2, \bar{k})$, condition C2 holds because $V^P > 0$, and Proposition 3 ensures that no eligible separating contract yields positive lender profit. Finally, for $k(b) < k_2$, C2 holds because no eligible separating contract yields positive lender profit and no eligible pooling contract exists. To see the latter, observe that when $k(b) < k_2$, $\psi_{\min} > \psi_{\max}$. Thus, for all $\psi \geq \psi_{\min}$, we have

$$U(P(\psi), \psi) \leq U(v, \psi_{\min}) < U(v, \psi_{\max}) = k(g).$$

The constraint set is therefore empty, and no eligible pooling contract exists. This completes the verification of condition C2.

Payoff Uniqueness.

Each borrower type's net profit

$$U(q) \;=\; \Big[\max_{(p,\gamma,\theta)\in Y^*} n(\theta)\, u(q; p, \gamma) \;-\; k(q)\Big]^+.$$

Condition C2 ensures

$$\max_{(p,\gamma,\theta)\in Y^*} n(\theta)\, u(q; p, \gamma) \;\leq\; k(q) \quad \text{for all } q,$$

so $U(q) = 0$ for every borrower type. Moreover, C2 uniquely pins down lender profit V.

□

Proposition 6

Proof. If $k(g) \in \big(0,\, v - c\big)$, then

$$k_0 - \bar{k} = k(g) + n(\theta^*)c - \frac{v}{v-c}k(g) = [m(\theta^*)(v-c) - \theta k(g)]\frac{\theta c}{v-c} > 0,$$

so $k_0 > \bar{k}$.

Existence.

We construct the equilibrium as follows. Define borrowers' utility u, lenders' matching surplus v as in C1, and define the set of eligible contracts Y as in C2. Set

$$V = \begin{cases} V^*, & k(b) \geq k_0, \\ V^S, & k(b) \in [\bar{k}, k_0), \\ 0, & k(b) < \bar{k}, \end{cases} \qquad Y^* = \begin{cases} \{(p^*, \delta_g, \theta^*)\}, & k(b) \geq k_0, \\ \{(p^S, \delta_g, \theta^S)\}, & k(b) \in [\bar{k}, k_0), \\ \emptyset, & k(b) < \bar{k}. \end{cases}$$

Condition C1 holds by construction of u and v. It remains to verify C2. If (p, γ, θ) is any eligible pooling contract, then the separating contract (p, δ_g, θ) is also eligible since with $a = 0$, $\Psi(p, \gamma) = \Psi(p, \delta_g) = 1$. If $m(\theta) = 0$, the lender profit generated by (p, γ, θ) is zero; if $m(\theta) > 0$, (p, δ_g, θ) yields strictly higher lender profit, so (p, γ, θ) either generate non-positive lender profit or is strictly dominated by a separating contract. Thus, pooling contracts cannot be profitable deviations. Having excluded pooling, it suffices to show that the contract in Y^* maximizes lender profit among eligible separating contracts and non-participation. This follows from Proposition 2 when $k(b) \geq k_0$ and from Proposition 3 when $k(b) < k_0$. Hence, C2 holds.

The proof of payoff uniqueness follows the same argument as in Proposition 5.

□

Proposition 7

Proof. The first-order derivative of the log objective function with respect to ψ is given by

$$D_\psi \log \hat{V}^P\big(P(\psi), \psi\big) = -\frac{1}{1 - \epsilon\Big(n^{-1}\Big(\frac{k(g)}{U(p,\psi)}\Big)\Big)}\left(\frac{1-a}{a}\cdot\frac{1}{\psi} + \frac{1}{\psi - \frac{k(g)}{k(b)}}\right)\Bigg|_{p=P(\psi)}$$
$$+ \frac{\frac{c}{v-c}}{\Big(\psi - \frac{v}{v-c}\frac{k(g)}{k(b)}\Big)\Big((1-a)\Big(\psi - \frac{v}{v-c}\frac{k(g)}{k(b)}\Big) + \frac{c}{v-c}\Big)}.$$

It is easy to verify that $D_\psi \log \hat{V}^P(P(\psi), \psi)$ increases in a. Hence, there exists an optimal pooling contract $(\tilde{p}^P, \tilde{\gamma}, \tilde{\theta}^P)$ with $\tilde{\psi} \geq \psi > 1$. From equation (9), we obtain $\tilde{p} \leq p$. $\square$

Proposition 8

Proof. When the matching elasticity decreases from α to $\tilde{\alpha}$, ψ^*_α increases, since $D_\psi \log \hat{V}^P(P(\psi), \psi)$ is decreasing in α when the queue length lies within the Cobb–Douglas region of the matching function. In contrast, ψ^*_1 and $\hat{\psi}$ remain unchanged. When the matching efficiency increases from A to $\tilde{A}$, $\hat{\psi}$ rises, while ψ^*_1 and ψ^*_α stay constant. Hence, overall optimal selectiveness increases.

From equation (9), we have $\tilde{p} \leq p$: the more selective acceptance rule under $\tilde{m}$ allows a lender to offer a lower price. By equation (4), this implies a lower share of good assets in the applicant pool, $\tilde{\gamma}(g) \leq \gamma(g)$.

$\square$

Proposition 9

Proof. It is easy to verify that $D_\psi \log \hat{V}^P(P(\psi), \psi)$ decreases in v. Hence, there exists an optimal pooling contract $(\tilde{p}^P, \tilde{\gamma}, \tilde{\theta}^P)$ with $\tilde{\psi} > \psi > 1$. From equation (9), we obtain $\tilde{p} < p$. $\square$