Fintech Expansion*

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August 2023

Abstract

I study credit market outcomes with different competing lending technologies: A fintech lender that learns from data and is able to seize on-platform sales, and a banking sector that relies on physical collateral. Despite flexible information acquisition technology, the endogenous fintech learning is surprisingly coarse—only sets a single threshold to screen out low-quality borrowers. As the fintech lending technology improves, better enforcement harms, while better information technology benefits traditional banking sector profits. Big data technology enables the fintech to leverage data from its early-stage operations in unbanked markets to develop predictive models for expansion into new markets.

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

Keywords: FinTech, Banking Competition, Information Acquisition, Digital Economy, Big Data

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1 Introduction

Following the Great Recession, the global banking industry has undergone major transformation due to stricter regulations and increased competition from fintech and bigtech sectors.[1] These new players provide distinctive front-end services and have revolutionized credit information processing through data and machine learning (Berg, Burg, Gombović, and Puri, 2020; Gambacorta, Huang, Li, Qiu, and Chen, 2023; Ghosh, Vallee, and Zeng, 2021).[2] In the U.S., they have grown rapidly (TransUnion report and Berg, Fuster, and Puri, 2021), with high growth rates for business lending (43.1% annually) and Buy-Now-Pay-Later (BNPL) loans (over 100% annually). The long-term effects of digital disruption on traditional banks remain uncertain, particularly as the aggressive entry of bigtechs could potentially render the traditional banking sector' legacy technologies and branch networks obsolete.

Fintech lending—which encompass both fintech and bigtech players in this paper—differs from bank lending in many ways, especially in small business loans (a key area within fintech). For example, as a payment processor, Square provides ***revenue-based loans*** to businesses like food trucks. These loans are repaid automatically by deducting a percentage from the daily sales, and are also available at Amazon and PayPal; as quoted from Square's website:

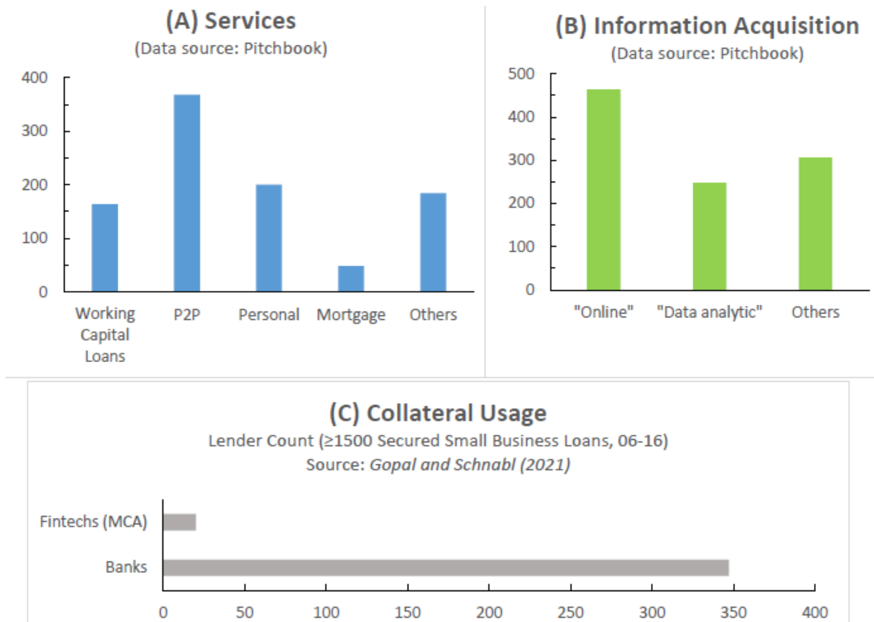
> "A fixed percentage of your ***daily card sales*** is automatically deducted until your loan is fully repaid...Loan eligibility is based on a variety of factors related to your business, including its payment processing volume, ***account history***, and payment frequency...applying for a Square loan ***doesn't a ect your credit score***."

Square's payment service enables conveniently collecting the incoming sales that flow through, and at the same time accumulating past activities for information acquisition. On the other hand, traditional banks do not have alternative data like the truck's real-time location to predict future sales. More fundamentally, even with this information, seizing cash flows is difficult for banks. Although both sales in-processing (in Square's case) and bank deposits are liabilities of the lender owed to the merchant borrower, deposits are more under the business's control (Hart and Moore, 1994; Kiyotaki and Moore, 1997) while sales in-processing are more under Square's control before being sought after by the bankruptcy estate, if default occurs. As a result, bank lending heavily relies on ***physical collateral*** (see small firms in Lian and Ma, 2021; Berger and Udell, 1998), such as the truck in this example.

[1] Fintechs serve customers of solid credit scores (Buchak, Matvos, Piskorski, and Seru, 2018; Tang, 2019; Di Maggio and Yao, 2021), suggesting competition with banks.

[2] Closest to this paper involves on-platform activities and transactions data, besides the mentioned studies, see also Ouyang (2021); Liu, Lu, and Xiong (2022).

Figure 1: Fintech Lenders Summary



A textual analysis of Pitchbook's company descriptions identified 867 fintech lenders and further classified their business models based on **Services (A)** and **Technology (B)**. See Online Appendix 7.1 for details. **Collateral usage (C)** is based on Gopal and Schnabl (2022), and shows a small presence of fintechs—mainly against merchant cash advances (revenue-based loans).

Data-driven lending is prevalent among fintech lenders. A textual analysis of Pitchbook's company descriptions reveals that fintechs often extend their credit based on sales, invoices, and receivables (Panel A of Figure 1), with a strong focus on information acquisition (Panel B). Additionally, the secured lending sample in Gopal and Schnabl (2022) reveals that fintechs rarely uses physical collateral: Their Table 2, partially reproduced in Panel C, shows that only 20 fintechs have issued over 1500 secured small business loans during 2006–2016; moreover, main fintech presence involves revenue-based loans (merchant cash advances).

This paper introduces a novel credit market competition framework, in which a fintech with a distinct cashflow-based enforcement competes against the traditional collateral-based lending. Existing studies often adapt canonical credit competition between banks, with the fintech having a different screening precision (He, Huang, and Zhou, 2023), or apply industrial organization (IO) frameworks to capture heterogeneous lending services in a reduced-form way (Chu and Wei, 2021). However, accumulating evidence show that bank and fintech lending are different and each would serve specific borrowers better, and unresolved issues remain such as mixed evidence on equilibrium prices upon fintech entry (Fuster, Plosser, Schnabl, and Vickery, 2019; Tang, 2019). With an emphasis on different lending technologies, this paper aims to offer fresh insights.

In my model, a borrower uses her own funds w and finances the investment shortfall $1 - w$ through debt to generate cash flow a, where a is private information. The two types w and a respectively represent the observable (LTV) and latent credit qualities. Within each market indexed by the observable type w, two lenders—a bank and a fintech—simultaneously decide whether to make an offer, and if yes, the corresponding interest rate. Lending is subject to *limited enforcement*, meaning that borrowers at most repay what the lender could enforce. Importantly, when choosing lenders, borrowers thus compare the *actual borrowing cost* (considering that she may abscond).

Lenders differ in enforcement technologies, which lead to their different evaluations of the same borrower. The bank collateralizes the physical asset, which has constant collateral value (in the baseline). This implies that borrower quality to the bank solely depends on wealth w; consequently, low-wealth markets become unbanked in the spirit of Holmstrom and Tirole (1997). In contrast, the fintech can seize a fraction of cash flows thanks to front-end service like Square, but does not take physical collateral due to its personnel-light business model. As a result, the fintech values borrowers with high productivity a which substitutes for w quality (LTV).

Low-productivity borrowers prefer defaulting on the fintech over collateralized bank loan, thus exposing the fintech to adverse selection. I assume that fintech lending features powerful information acquisition, as it benefits from recent revolutions of machine learning, big data, and more. In the model, the fintech can learn about *any partition* of borrower productivity at an entropy cost, allowing it to categorize borrowers as desired and offer tailored quotes. One model extension allows for cross-market information spillover to forecast new markets with acquired information. Consistent with confidential algorithms, information acquisition is *unobservable* to the bank, implying that the fintech does not commit to an information structure during credit market competition.

My model is best suited for cash flow-based fintech lending to small businesses like Square. However, the insights apply to a broad range of fintech lending. Fintechs offering unique services can enforce via exclusion threats, and the borrower's latent quality is her willingness to repay for future access. Examples include Alibaba Group's small merchant platform and "Buy Now Pay Later" services.[3] The model is also relevant to fintech lending tied to specific

[3] Ant group, the financing arm of the Alibaba group, does not deduct sales for loan repayment but controls access to the parent company's merchant platform.

"scenarios," where the borrower's latent type represents the actual use of the funds.

The main result of my model, as shown in Theorem 1, is that information acquisition is surprisingly "coarse." In the unique equilibrium, the fintech only acquires a "single-threshold" structure to screen out borrowers below the threshold, despite having the potential to secretly acquire more information to offer tailored loans and steal customers (from the bank), and lenders adopt mixed strategies in interest rate offering. The coarse learning result is driven by competition and debt contracts. The fintech does not benefit from extra information (beyond the lending threshold), as we illustrate by showing that it will not adjust equilibrium quotes even if secretly knowing the borrower's true productivity. First, any high quotes incurring borrower default are the same to the fintech, whose payoff only depends on the enforceable amount rather than the quote. Second, across lower quotes that the customer fully repays, competition from bank is so fierce that a higher quote to extract the borrower is exactly offset with a lower chance of winning her as customer, making the fintech indifferent either. Last, these two regions share a same knife-edge quote, so the fintech is indifferent over the original equilibrium support and additional information does not affect its optimal strategy.

Fundamentally, the "coarse" learning result arises because the bank does not suffer from the winner's curse, a key property that holds generally in my model even if the bank can seize some cash-flows. Hence, the bank ignores any information about productivity implied by the quote and only reacts to the fintech's quote itself. This leads to intense bank competition faced by the fintech, eliminating the benefit to acquire additional information. Moreover, as information comes at a cost, the single-threshold partition and resulting credit market competition represent the only equilibrium outcome.

My model thus explains why unsecured lending is "coarse." In practice, fintech and bigtech internal ratings are often in coarse categories; and more broadly, credit card lenders with ample in-house data still offer the same rates to observably different customers. Traditional models with a "common value" setting would predict the opposite since information brings monopoly power (Sharpe, 1990), while my model predicts "coarse" unsecured lending because the competition from the secured lending option eliminates information rent. As a testable implication, in response to different degrees of competition environment, unsophisticated interest rates would be offered at loan origination to compete for the customer, while once the loan is granted, price discrimination may arise via fees.

The credit market equilibrium features lender specialization. Bank credit depends on observable credit qualities, while fintech lending gives high-productivity borrowers another chance: those previously unbanked are picked up as the "invisible primes" (Di Maggio, Ratnadiwakara, and Carmichael, 2021), and wealthy borrowers with access to bank credit enjoy lower interest rate due to competition.

My model has unique implications for fintech disruption. Canonical "common value" competition theories predict negative impacts of fintech entry on traditional lending, as fintechs with better information technology would eliminate traditional lender's information rent. In contrast, fintech in my model competes on a different dimension, delivering more nuanced implications depending on the specific fintech technologies under question. Better "enforcement" technology hurts traditional lending by intensifying competition, but better "information" technology can benefit it—a lower information cost enables the fintech to better identify high-productivity customers, leading to a less intense competition. In the long run, both lending services are likely to coexist and compete.

Introducing information spillovers across markets, the last section models the big data technology that accumulates data for developing algorithms with out-of-market predictability. In particular, the early-stage fintech industry faces limited data and high information costs, and only profits by issuing high-interest, risky loans to unbanked populations. Data collected from these early-stage operations can be used to develop predictive models that identify high-quality borrowers in wealthier market, thus facilitating expansion.

Related Literature

The paper contributes to the growing ***fintech literature*** and more broadly connects with the ***banking IO literature*** and ***auction theory***. Limited enforcement borrows from ***incomplete contracts*** (Hart and Moore, 1994; Hart, 1995): traditional lending relies on physical collateral,[4] and the fintech's service allows for enforcement and information acquisition, as motivated by empirical evidence.[5] Closest to my paper, and related to portable transactions data under open banking,[6] Ghosh, Vallee, and Zeng (2021) demonstrate a synergy between payment data and fintech credit extension; Gambacorta, Huang, Li, Qiu, and Chen (2023) find that bigtech credit strongly reacts to changes in firm characteristics instead of house prices, so its lending relies on data rather than collateral.

The different enforcement setting complements the ***canonical credit competition*** (Broecker, 1990; Hauswald and Marquez, 2003) that are applications of the ***common value auction***.[7] In

[4] See Kiyotaki and Moore (1997); Kehoe and Levine (1993); Rampini and Viswanathan (2010).

[5] Even basic footprints are as effective as credit scores (Berg, Burg, Gombović, and Puri, 2020), let alone the transactions data (Square) or when customers "live there lives" on its App (Liu, Lu, and Xiong, 2022).

[6] This burgeoning literature includes He, Huang, and Zhou (2023); Goldstein, Huang, and Yang (2022) and Babina, Buchak, and Gornall (2022).

[7] To name a few, Milgrom and Weber (1982); Hausch (1987); Kagel and Levin (1999); Banerjee (2005).

classic frameworks, lenders are asymmetrically informed about the borrower's underlying quality from their own credit assessment. Better information thus brings monopoly power (Sharpe, 1990), because competitors are concerned about the "*winner's curse*". In other models, lenders may use collateral to recover loss (Dell'Ariccia and Marquez, 2006). Closest to this paper is Sengupta (2007) showing that less informed entrants use collateral in credit competition. These theories remain within the common value auction applications, where a trade-off exists between utilizing information versus collateral to address adverse selection, and collateral is costly due to inefficient liquidation.[8] In my paper, collateral serves to enforce and liquidation never occurs; collateral and information-based lending are different services that suit different customers, with no clear superiority of one over the other.

My model is in a unique setting of ***auction with flexible information acquisition***, whereas the literature primarily focuses on binary or one-dimensional choice (Persico, 2000; Shi, 2012). The analysis on flexible information acquisition remains challenging; for example, Kim and Koh (2022) consider independent private value auctions with binary underlying values. To effectively model big data and machine learning technologies, I adopt a setting with a continuum of underlying values and the information acquisition technology enables learning any partitions, akin to the decision tree models. The single-threshold structure, which does not rely on a (pure) private value setting, arises as an endogenous outcome and potentially paves the way for the development of more advanced models in the future.

Theories on fintech lending are new,[9] and several recent papers point out platforms' advantage to enforce cash flows: Li and Pegoraro (2022) highlight bigtechs' advantageous screening as low type borrowers self select to unsecured bank lending, Bouvard, Casamatta, and Xiong (2022) jointly model the platform's decisions on credit as well as access fees, and Boualam and Yoo (2022) study fintech's decision on whether to collaborate with banks. In contrast, I explore how the platform flexibly acquires information and tailors lending.

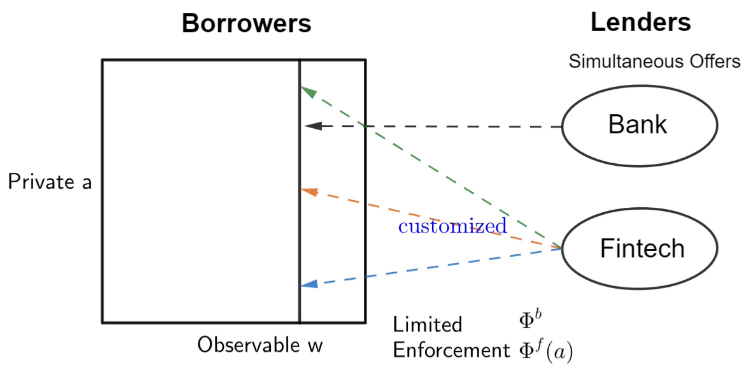
2 The Model

We present the main model and explain the key differences from the canonical framework.

[8] This is consistent with the patterns that collateral requirements fall as lender information improves; see Boot and Thakor (1994); Petersen and Rajan (1994); Berger and Udell (1995).

[9] Vives and Ye (2021) examine how the diffusion of information technology affects lending competition. Parlour, Rajan, and Zhu (2022) argue that fintech competition in payments disrupts the natural information spillover for lending within the traditional bank. On open banking, He, Huang, and Zhou (2023) emphasize borrower control, while Goldstein, Huang, and Yang (2022) consider the endogenous responses from bank's deposit funding (liability side) to bank's loan making (asset side).

Figure 2: Model Scheme



2.1 Model Setup

Figure 2 summarizes the model. A bank and a fintech compete by making simultaneous loan offers. With ***limited enforcement***, a borrower at most repays what the lender could enforce—collateral value for the bank versus a fraction of sales for the fintech. Additionally, the fintech flexibly acquires information about sales to customize offers.

2.1.1 Borrowers

At $t = 0$, each borrower has one project that costs one dollar to install, but she only has $w \in [0, 1]$ and thus needs to finance the shortfall $1 - w$.[10] We assume that borrowers enjoy sufficiently large private benefit from their projects, so that they always want to borrow and produce. At $t = 1$, the project generates cash flows $a \in [\underline{a}, \overline{a}]$.

The two-dimensional borrower type (w, a) corresponds to the observable and latent credit qualities in practice. The amount w is observable and captures the loan-to-value (LTV) ratio.[11] Productivity a is the borrower's private information at $t = 0$ (but the fintech can costly learn), and becomes publicly known at $t = 1$. Henceforth, we call each w a market, and the baseline model considers competition within each w.

The distribution of markets w is characterized by cumulative distribution function (CDF) $H(w)$ and probability distribution function (PDF) $h(w)$. Within market w, CDF $G(a|w)$ and PDF $g(a|w)$ summarize the prior distribution of a. Model extension (Section 4) introduces cross-market predictability with implicit independence between w and a.

[10] This is consistent with the macro-finance literature (Holmstrom and Tirole, 1997; He and Krishnamurthy, 2012) where a financially constrained entrepreneur fully invests her own wealth into the project.

[11] The model applies to scalable projects if there is no signaling via investment size.

Limited enforcement As alternative lending mainly serves households and small businesses, limited enforcement is a key friction. Specifically, a borrower walks away from the promised repayment whenever she could at $t = 1$. Let Φ^j denote the maximum amount that lender $j \quad \{b(\text{ank}), f(\text{intech})\}$ could seize. For a loan of $1 - w$ offered at an interest rate $r^j \geq 0$ by this lender, the *actual* repayment is

$$\min\left\{\left(1 + r^j\right)(1 - w), \Phi^j\right\}. \tag{1}$$

To focus on the enforcement friction, the paper assumes that borrowers have enough resources; with renegotiation, this avoids any inefficient liquidation (for details, see later discussion in Section 2.1.2).

Therefore, from the borrower's perspective, the actual borrowing cost is Eq. (1). When provided with both the bank's quote r^b and the fintech's quote r^f, the borrower selects the one with the lower actual cost:

$$\min\left\{\underbrace{\min\left\{\left(1 + r^b\right)(1 - w), \Phi^b\right\}}_{\text{repayment to bank}}, \underbrace{\min\left\{\left(1 + r^f\right)(1 - w), \Phi^f\right\}}_{\text{repayment to fintech}}\right\}. \tag{2}$$

As the other side of the same coin, lender j is unwilling to lend more than the enforcement limit. Limited enforcement constrains the ex ante lending capacities, implying that lenders engage in price competition under asymmetric capacities from different enforcement.

Lenders hence value the same borrower differently, and this contrasts with the canonical credit competition models (Broecker, 1990; Hauswald and Marquez, 2003) that are applications of common value auction. The model also differs from monopolistic competition with differentiated goods and *inelastic substitutability* from customer preference, such as the Hotelling model. Here, the borrower views the two financing options as *fungible*, and the "suitability" of financing options work as capacity constraints on the lender side.

Data versus collateral In contrast to traditional lending which relies on physical collateral ("land" in Kiyotaki and Moore, 1997), the new fintech lending features innovative enforcement and information acquisition. Square loans are automatically repaid by a percentage of food sales that flow through the payment processor, and similar loans are available from PayPal and Amazon.[12] Seizing small businesses' cash flows is difficult for banks, as de-

[12] These loans are called "PayPal Working Capital" (link) and "Amazon Lending" (link), respectively.

posits are more under the business's control while sales in-processing are more under Square's control,[13] before being sought after by the bankruptcy estate (if default occurs). This "data versus collateral" lending pattern is documented by Gambacorta, Huang, Li, Qiu, and Chen (2023) and applies to a wide range of fintech lending. For example, platforms like Alibaba and "Buy Now Pay Later" services are able to enforce via exclusion, and its effectiveness depend on the borrower's unobservable preference for the service. Other fintech lending is linked to specific "scenarios," and the borrower's latent type is her usage of the funds.

2.1.2 Lenders

There are two lenders, a bank and a fintech, both with unlimited funding at unit cost. Lending is restricted to standard debt contracts. Both lenders simultaneously choose whether or not to make a loan offer, and the interest rate if the offer is made.

Bank The limited enforcement follows Hart and Moore (1994) and Kiyotaki and Moore (1997). Borrowers can abscond with cash but not physical capital, and the bank can liquidate the collateral if the borrower defaults on a promised interest rate of $r^b(w)$. Suppose that the collateral is worth θ to the bank, with θ being a publicly known constant. Then right before repayment, the borrower can renegotiate the payment down to the bank's reservation value of θ, assuming that the borrower has all the bargaining power (due to inalienbility of human capital). Hence, the maximum repayment that the bank can enforce is

$$\Phi^b = \theta. \tag{3}$$

We assume $\underline{a} \geq \theta$, i.e., a borrower always has enough resource to repay the bank and therefore inefficient liquidation never occurs.

Without loss of generality, we can focus on renegotiation-proof contracts,

$$\underbrace{\left(1 + r^b(w)\right)}_{\text{unit gross rate}}(1 - w) \leq \underbrace{\theta}_{\text{collateral value}}, \tag{4}$$

which are *riskless* absent uncertainty in collateral value θ. Moreover, the bank lends to the borrower if and only if the collateral value θ is enough to cover the financing needs $1 - w$, and borrowers with lower w become "unbanked." Formally, denote by $m^b(w)$ the probability

[13] Payment processors connect bank accounts and networks (VISA, Mastercard, Amex, Discover) and deduction happens on sales in-processing before they become bank deposits.

that the bank makes an offer, so $m^b(w) = 1$ when $w \geq 1 - \theta$ and $m^b(w) = 0$ otherwise. When $w \geq 1 - \theta$, the bank chooses $r^b(w)$ subject to the collateral constraint Eq. (4), or

$$r^b(w) \leq R^b(w) \equiv \frac{\theta}{1 - w} - 1, \tag{5}$$

where $R^b(w)$ is the ceiling rate implied by the collateral value. As mixed strategy may arise, denote by $F^b\left(r^b; w\right)$ the CDF distribution of the bank's interest rate offering. The formal notation for bank participation $m^b(w)$ will be omitted for the rest of the paper.

Remark 1. In my model with limited enforcement, from the bank's perspective the borrower quality only depends on the collateral value θ and LTV w; in other words, the borrower's underlying productivity a has *no fundamental value* to the bank. This extreme modeling contrasts with the canonical common-value credit competition theories, in order to highlight the difference in fintech versus bank lending. However, as shown in Section 3.2, the key insight does not rely on this extreme setting. My result holds even if the bank can also enforce on some a, i.e., $\Phi^b = \theta + \gamma a$ for small $\gamma > 0$. For example, productivity may correlate with the collateral value, or the bank has some bargaining power to leverage the fact that more productive borrowers are less willing to lose capital (Besanko and Thakor, 1987).

To highlight the fintech's information technology, I assume that the bank cannot acquire information about borrower productivity a.

Fintech The fintech lender represents a diverse range of alternative lenders, including fintechs, bigtechs, platforms, that share the following business model. The fintech does not collateralize the physical capital, which is consistent with its lean personnel structure in practice and the small fintech presence in secured small business lending (Gopal and Schnabl, 2022). Instead, the fintech lender can seize a fraction $\beta \in (0, 1]$ of the borrower's cash flow a at $t = 1$. For example, Square as a payment processor collects repayments by deducting a fixed percentage (β) from the incoming sales (a) until the loan is paid off.

Hence, the maximum amount that the fintech could enforce is

$$\Phi^f(a) = \beta a, \tag{6}$$

and the actual repayment to a fintech loan of $1 - w$ at interest rate $r^f(w)$ is

$$\min\left\{\left(1 + r^f(w)\right)(1 - w), \beta a\right\}. \tag{7}$$

For later analysis, it is convenient to introduce

$$R^f\ (a; w) \equiv \frac{\beta a}{1 - w} - 1, \tag{8}$$

$$\underline{a}^f\ (r; w) \equiv \frac{(1 - w)(1 + r)}{\beta} \tag{9}$$

to denote respectively the maximum fintech quote R^f that a type (w, a) borrower fully repays, and the lowest type $\underline{a}^f$ who fully repays the fintech quote of r.

Payment processors enjoy the advantage to directly seize cash flows.[14] For Ant Group (Alibaba) that enforces via an exclusion threat, Eq. (7) also applies. To see this, suppose that a merchant borrower is less productive off the Alibaba's platform and only generates $(1 - \beta)a$; then, Alibaba controlling the platform access has all the bargaining power in the negotiation and can enforce up to βa from the borrower. Similarly, enforcement is better for high latent quality borrowers (who care more about maintaining platform access.)

Fintech lending features powerful information technology at $t = 0$. I focus on information acquisition that results in partitions, akin to decision tree models in machine learning (see Bryzgalova, Pelger, and Zhu, 2021). Specifically, the fintech *secretly* chooses a partition about borrower productivity a in market w

$$P^w \equiv \left\{A^i\,(w) \quad [\underline{a}, \overline{a}]\right\}$$

at the Shannon entropy cost, which measures the "quantity of information." A partition divides the set into disjoint events ($A^i \cap A^i \;=\quad$ for $A^i \;=\; A^i$) and covers the entire set ($\bigcup_{A^i \quad P} A^i = [\underline{a}, \overline{a}]$). Hence, the fintech lender can privately categorize borrowers' productivity in an arbitrary way and learn which category A^i the borrower belongs to. For example, with $\{[0.3, 0.4) \bigcup [0.6, 1]\,, [0.4, 0.6)\}$ (for $a \quad [0.3, 1]$) the fintech knows whether the borrower's productivity lies between 0.4 and 0.6.

Information acquisition allows the fintech to customize lending strategies. For each event $A^i\,(w) \quad P^w$, the fintech chooses the probability to make an offer, denoted by $m^f\,(A^i; w)$, and the CDF distribution of its interest rate $F^f\,\left(r^f\,|A^i\,(w)\,; w\right)$ upon offering. Importantly, the fintech does not commit to an information structure during credit competition, because information acquisition is *unobservable*. Hence, in equilibrium, the fintech has no profitable deviations by secretly adjusting its information acquisition and follow-on lending strategies.

[14]See Footnote 12 for comparison between sales in-processing and bank deposits. Moreover, Square observes account activities and uses covenants to reduce a borrower's potential diversion to other payments.

Fintech's entropy learning cost and cross-market predictability Let $I(\cdot)$ represent the Shannon entropy which measures the "information quantity", i.e., the distance between the posterior (after information acquisition) and the prior distribution,

$$\underbrace{I\left(P^{w}\right)}_{\text{entropy of info structure}} \equiv \underbrace{-\mathrm{E}\left[\log g\left(a\right)\right]}_{\text{prior}} + \mathrm{E}\left[\underbrace{\mathrm{E}\log g\left(a \middle| A^{i}\left(w\right)\right)}_{\text{posterior}}\right].$$

The cost of acquiring P^{w} in market w is

$$C\left(P^{w}, w\right) \equiv \underbrace{c}_{\text{unit cost}} \cdot \underbrace{I\left(P^{w}\right)}_{\text{entropy of info structure}} dw. \tag{10}$$

where c parameterizes the difficulty to acquire information.

Section 4 introduces cross-market predictability: there, we interpret P^{w} as an algorithmic model developed in an *existing* market w, which could be used to identify the same categorical traits in another market $w\ = w$ at reduced information cost

$$C\left(P^{w}, w\ \right) = \delta \cdot C\left(P^{w}, w\right) = \delta \cdot cI\left(P^{w}\right) dw, \tag{11}$$

with $\delta\quad[0,1]$. The baseline case absent cross-market predictability is nested by $\delta = 1$.

2.2 Lender Payoffs

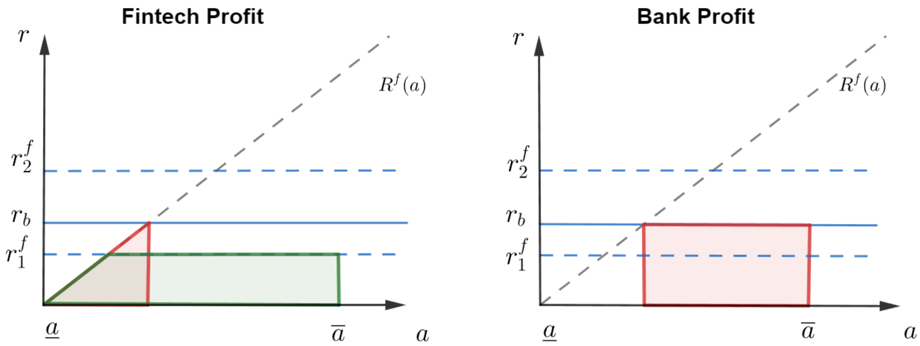
As explained, the borrower picks the lower effective cost as in Eq. (2). Under our assumptions on Φ^{b} and Φ^{f}, Eq. (2) can be simplified as

$$\min\left\{r^{b}, \min\left\{r^{f}, R^{f}\left(a\right)\right\}\right\}. \tag{12}$$

Figure 3 summarizes borrower choice and the resulting lender profits within market w. For illustration, the bank's quote is fixed at r^{b} and two cases of the fintech's quote are considered: $r_{1}^{f} < r^{b}$ (green) and $r_{2}^{f} > r^{b}$ (red). The upward sloping dashed line $R^{f}(a) \equiv \frac{\beta a}{1-w} - 1$ given in Eq. (8) is the maximum fintech rate that will be repaid as a function of productivity a.

In the first case where the fintech's quote is lower $r_{1}^{f} < r^{b}$, we have $r^{b} > r_{1}^{f} \geq \min\left\{R^{f}(a), r_{1}^{f}\right\}$ and all borrowers choose the fintech offer. The fintech profit in the left panel is shown in green area, while there is no bank profit in the right panel (because nobody goes to the bank). Regarding actual repayment in fintech profits, borrowers with low productivity, i.e.,

Figure 3: Borrower Choice and Lender Profits



Profits of the fintech (left) and the bank (right) shown as the shaded areas that integrate the actual repayment from borrowers who choose the lender. Two cases are considered, $r_1^f < r^b$ (green) and $r_2^f > r^b$ (red).

$R^f(a) < r_1^f$, default and repay $R^f(a)$, while others, i.e., $R^f(a) \geq r_1^f$ repay r_1^f.

In the second case where the bank quote is lower $r^b < r_2^f$, whoever choosing the fintech must have relatively low productivity with $R^f(a) < r^b < r_2^f$ so that the actual cost of borrowing from fintech—defaulting and paying $R^f(a)$—is more attractive than paying r^b to the bank. The red areas show the resulting lender profits: the fintech profit (left panel) is the lower triangle that comes from low productivity borrowers who default, and the bank profit (right panel) comes from high productivity borrowers who repay r^b.

It is worth highlighting that only the fintech suffers from ***adverse selection***, while the collateralized bank loan is free of this risk. This aligns with a key empirical regularity that traditional bank loans in SMEs and micro-business sectors are often collateralized to mitigate business risk (Gopal and Schnabl, 2022). This feature is also different from canonical models where all lenders are subject to adverse selection under the "common value" setting.

In any market $w \geq 1 - \theta$, the bank's profit when quoting $r^b \leq R^b(w)$ is

$$\pi^b\left(r^b; w\right) \propto \sum_{A^i \in P^w} \mathrm{P}\left(A_i\right) \left[\underbrace{1 - m^f\left(A_i\right)}_{\text{no fintech offer}} + \underbrace{m^f\left(A_i\right)}_{\text{fintech offer}} \cdot \underbrace{\int_{\underline{a}^f\left(r^b\right)}^{\overline{a}}}_{\text{high } a} \mathbf{1}_{A^i} \underbrace{\left[1 - F^f\left(r^b \middle| A^i\right)\right]}_{\text{bank quote is lower}} dG(a)\right] r^b. \quad (13)$$

A scaling term of market demand $(1 - w)\, dH(w)$ is omitted (so "$\propto$" is used), and the right-hand-side is the profit rate per unit dollar lent. The bank forms an expectation over the fintech's private information (P^w) and mixed strategy: upon each $A^i(w)$, the bank faces competition with probability $m^f(A^i)$ when the fintech makes an offer; in competition, as illustrated in the right panel of Figure 3, the bank wins the customer when both its quote is lower, $r^b < r^f$ (which occurs with probability $1 - F^f\left(r^b\right)$), and the borrower's productivity is relatively high, $a > \underline{a}^f\left(r^b\right)$ so that she does not prefer defaulting with the fintech. (Recall $\underline{a}^f(r;w) \equiv \frac{(1-w)(1+r)}{\beta}$ in Eq. (9) is the lowest type who fully repays r to the fintech.)

For the fintech lender, given that $a \in A^i$, its expected profits when quoting r^f is

$$\pi^f\left(r^f \middle| A^i; w\right) = \underbrace{\left[1 - F^b\left(r^f\right)\right]}_{\text{fintech quote is lower}} \mathsf{E}\left[\min\left\{R^f(a), r^f\right\} \middle| A^i\right] + \underbrace{\int_0^{r^f}}_{\text{fintech quote is higher}} \left[\underbrace{\int_{\underline{a}}^{\underline{a}^f\left(r^b\right)} \frac{\mathbf{1}_{A^i}}{\mathsf{P}\left(A^i\right)} R^f(a)\, g(a)\, da}_{\text{low } a\text{: adverse selection}}\right] dF^b\left(r^b\right). \tag{14}$$

When $w < 1 - \theta$, the fintech is a monopolist, and the profit is

$$\pi^f\left(r^f \middle| A^i; w\right) = \mathsf{E}\left[\min\left\{R^f(a), r^f\right\} \middle| A^i\right]. \tag{15}$$

Using Eq. (14)-(15), one can derive the fintech's expected lending profits before knowing borrower category A^i, and net profits that take into account the information cost.

2.3 Comparison with Literature

It's worth pausing to discuss how the productivity, and its information, affects the credit market competition. In the baseline setting that highlights different lending, information about productivity a only reveals the fintech's customer quality through enforceable repayments, while it is inconsequential on customer quality to the bank who cares about collateral only. Nevertheless, as will be explained in Section 3.2, the key insight still holds if the bank could additionally enforce some cash flows and the fintech is more sensitive to adverse selection.

The difference in enforcement technologies separates my paper from the existing credit market competition models that are built on a common value auction setting (Broecker, 1990; Hauswald and Marquez, 2003; He, Huang, and Zhou, 2023). In those models, lenders offer the same product and value the credit quality information the same way. Even when considering differentiated lending and customer preferences (for example, lender location in Vives and Ye, 2021), credit competition still falls within the framework of common value auction, with the necessary adjustment to account for inelastic substitutability between options. In contrast, I highlight that *lenders* have different preferred borrower types due to different lending technologies, but financing options are perfectly *fungible to borrowers*. This generates unique predictions in my model: as emphasized in Section 3.3, while typically a larger gap in information technology hurts the less informed lender, in my model an improved information technology in fintech lending may instead benefit the bank.

2.4 Parameter Assumptions

To focus on relevant cases with interesting economic implications, I make the following assumptions throughout the paper.

Assumption 1. *The parameters of my model satisfies the following conditions.*

1. *$\underline{a}$ is relatively low with $R^f(\underline{a};\overline{w}) < 0$, so that the fintech su ers from "adverse selection."*
2. *$\mathrm{E}\left(R^f(a);1-\theta\right) > 0$, so the fintech enters unbanked markets; in markets where the bank is present, the medium type is positive NPV to the fintech, $R^f\left(a^{med};1-\theta\right) \geq 0$.*
3. *Unit learning cost c is relatively small $c \leq \overline{c}$.*

We further impose the following assumption to ensure a well-behaved mixed strategy equilibrium (to avoid "ironing" in Myerson, 1981).

Assumption 2. *$G(a)$ is regular, i.e., the virtual valuation $a - \frac{1-G(a)}{g(a)}$ weakly increases.*

The following assumption imposes regularity conditions on the information cost function and the distribution functions of a and w to ensure the equilibrium is well-behaved.

Assumption 3. *We impose two extra regularity conditions.*

1. *The function $\frac{G(a)}{1-G(a)}$ is log-concave (convex) when $a < (>) a^{med}$;*
2. *$sgn\{\frac{\partial\left[(1-w)h(w)\min\left\{r,R^f(a)\right\}\right]}{\partial w}\} = sgn\{\frac{\partial \min\left\{r,R^f(a)\right\}}{\partial w}\}$.*

3 Information Acquisition and Fintech Disruption

This section analyzes credit market equilibrium within a market, assuming no inter-market information spillover. Strikingly, despite having flexible and unobservable information acquisition, the fintech lender's optimal information structure only involves screening out borrowers below a single threshold. Additionally, a better fintech's information technology could actually benefit the competitor bank.

3.1 Equilibrium Definition

As explained, the fintech lender's strategy profile includes information acquisition strategy $P^{f,w}$ and lending strategy $\left\{m^f\left(A^i\right), F^f\left(r^f\left|A^i\right.\right)\right\}_{A^i \quad P^{f,w}}$, while the bank offers a quote according to the strategy $F^b(r)$ in market with $w \geq 1-\theta$ and exits from all markets with $w < 1-\theta$. We define the credit market competitive equilibrium as follows.

Definition 1. (Credit Competition Equilibrium) Consider a market with $w \geq 1-\theta$. In a credit market competitive equilibrium, we have:

1. Given the fintech's strategy, the bank's strategy solves following problem:

$$\max_{r^b(w) \leq R^b(w)} \pi^b\left(r^b; w\right), \tag{16}$$

   where $\pi^b\left(r^b; w\right)$ is given by Eq. (13);

2. Given the bank's strategy, the fintech solves the following problem

$$\max_{P^{f,w}} \sum_{A^i \quad P^{f,w}} \mathsf{P}\left(A^i\right)\left[\max_{m^f\left(A^i\right), r^f\left(A^i\right)} m^f\left(A^i\right) \pi^f\left(r^f\left|A^i\right.; w\right)\right] - C\left(P, w\right), \tag{17}$$

   where $\pi^f\left(r^f\left|A^i\right.; w\right)$ is given by Eq. (14) and $C\left(P, w\right)$ is given by Eq. (10);

3. A borrower (w, a) with two offers $\left\{r^b, r^f\right\}$ picks the lower offer $\min\left\{r^b, \min\left\{r^f, R^f\left(a\right)\right\}\right\}$. Otherwise, a borrower takes the only offer, if any, that she receives.

The equilibrium is in mixed strategies with $m^f, F^f\left(r\right)$, and $F^b\left(r\right)$, such that any lender is indifferent across all interest rate quotes on support. Under Assumption 2, the equilibrium is well-behaved: F^j's are over interval supports $[\underline{r}^j, \overline{r}^j]$ without interior atoms or gaps.

Definition 2. Consider a market with $w < 1-\theta$. In the equilibrium, the fintech is the monopolist lender who solves the following problem:

$$\max_{P^w} \sum_{A^i \quad P^w} \mathsf{P}\left(A^i\right)\left[\max_{m^f\left(A^i\right), r^f\left(A^i\right)} m^f\left(A^i\right)(1-w)\,\mathsf{E}\left[\min\left\{R^f\left(a\right), r^f\right\}\middle| A^i\right] dH\left(w\right)\right] - C\left(P; w\right). \tag{18}$$

The remainder of this section characterizes the equilibrium for any given w, implying that all equilibrium variables depend on w. For ease of exposition, I will omit this indexation w from now on (up to Section 4.2).

3.2 Optimal Learning: Screen Out

Granular information seems attractive to the fintech, who could then undercut the bank for the right customers at the right price, especially as information acquisition is unobservable. Surprisingly, the main finding of this paper (Theorem 1) is that the optimal fintech learning strategy is “coarse,” using a single cutoff to screen out borrowers below that threshold.

Theorem 1. *The equilibrium is unique. The fintech’s optimal information acquisition policy separates two intervals with an endogenous cuto* $\hat{a}$*:*

$$P^{f,w} = \{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\}, \tag{19}$$

so that the fintech rejects borrowers with $a < \hat{a}$ *and makes an o er upon* $a \geq \hat{a}$*.*

1. *When* $w \geq 1 - \theta$*, the bank always makes o er while the fintech makes o er when* $a \geq \hat{a}$*. The o ered interest rates* $\left\{r^b, r^f\right\}$ *are randomized over a common support* $\left[\underline{r}, R^b\right]$ *according to*

$$F^b(r) = 1 - \frac{\underline{r}}{r}, \tag{20}$$

$$F^f(r \,|a \geq \hat{a}) = 1 - \frac{G(\hat{a})}{1 - G(\max\{\underline{a}^f(\underline{r}), \hat{a}\})} \cdot \frac{R^b - r}{r}, \tag{21}$$

where $\underline{r}$ *satisfies* $F^f(\underline{r}\,|a \geq \hat{a}) = 0$*. The bank’s (fintech’s) CDF has a point mass (is open) at the upper bound* R^b*.*

2. *When* $w < 1 - \theta$*, the monopolist fintech o ers* $r^f = R^f(\overline{a})$ *to borrowers with* $a \geq \hat{a}$*.*

The endogenous screening threshold $\hat{a}$ *adopted by the fintech satisfies*

$$\underbrace{(1 - w)\,h(w)\,R^f(\hat{a})}_{MR:\ \text{profit from marginal type}} = \underbrace{c \log\left[\frac{1 - G(\hat{a})}{G(\hat{a})}\right]}_{MC:\ \text{marginal information cost}} \tag{22}$$

Proof. See Appendix 6.1. □

Intuition for the optimal screening with “single-threshold” structure *Competition* between different technologies and *debt contract* are the core forces behind the simple single-threshold structure. Consider the more intriguing case of $w \geq 1 - \theta$ with bank competition.

Additional information about a can benefit the fintech in two ways: customizing pricing and indirectly revealing the bank's strategy. The second inference effect is absent under the "private value" setting (relaxed in Remark 2).

Even more surprisingly, the first customization effect is also absent: in equilibrium, the fintech gains no advantage from knowing borrower quality a. To see this, given the bank's equilibrium strategy, the fintech's profits when quoting any r^f is:[15]

$$\underbrace{\int_{\underline{a}}^{\underline{a}^f(r^f)}}_{\text{low } a} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{\text{winning prob}} \cdot \underbrace{R^f(a)}_{\text{repayment}} dG(a) + \underbrace{\int_{\underline{a}(r^f)}^{\overline{a}} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^b\left(r^f\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^f}_{\text{repayment}}, \tag{23}$$

which includes two possible scenarios depending on whether the borrower defaults (the first term) or not (the second term); the green area in Figure 3 with $r^b > r^f$ displays these two parts of a.

With Eq. (23), I show that even if the fintech knows the borrower type a exactly, it is *indi erent* with any interest rate quote $\tilde{r}^f$ on the equilibrium support $\tilde{r}^f \quad \left[\underline{r}, R^b\right)$; hence "information" has no value because the fintech does not change its optimal strategy. To see this, consider the fintech's deviation payoff when it knows type a and varies the potential quote $\tilde{r}^f$, which ranges across two regions in analogous to those in Eq. (23) (there we fix r^f but integrate over types). In the first "high rate" region $\tilde{r}^f \geq R^f(a)$, the borrower defaults and repays βa under debt contract (analogous to the first term of Eq. (23)). Then the quote itself becomes irrelevant, and any quote in this region $\tilde{r}^f \geq R^f(a)$ leads to the same profit

$$\underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{\text{winning prob}} \cdot \underbrace{R^f(a)}_{\text{repayment}}.$$

In the second "low rate" region $\tilde{r}^f \leq R^f(a)$ (analogous to the second term of Eq. (23)), the borrower fully repays and the fintech solves the following problem (which is irrelevant of a):

$$\max_{\tilde{r}^f} \underbrace{\left[1 - F^b\left(\tilde{r}^f\right)\right]}_{\text{winning prob}} \cdot \underbrace{\tilde{r}^f}_{\text{repayment}}.$$

Given the bank's equilibrium strategy $F^b(r) = 1 - \frac{\underline{r}}{r}$, the fintech is indifferent across any

[15]If $R^f(\hat{a}) < \underline{r}$, there is an extra term $\int_{\hat{a}}^{\underline{a}^f(\underline{r})} R^f(a)\, dG(a)$ in the fintech's profits that was omitted for expositional convenience. The omitted term is the same in nature as the first term in Eq. (23) with $1 - F^b\left(R^f(a)\right) \equiv 1$, so the omission does not affect the analysis here.

quotes in this region $\underline{r} \leq \tilde{r}^f \leq R^f(a)$;[16] so competition essentially eliminates the potential advantage of a customized offer. Last, these two regions share the same knife-edge quote $\tilde{r}^f = R^f(a)$. Therefore, even with the knowledge of a, the fintech is indifference over the entire equilibrium support $[\underline{r}, R^b]$, so it has no incentive to learn additional information within $a > \hat{a}$.

Finally, price discrimination is valuable to the monopolistic fintech for $w < 1 - \theta$, but it can be achieved via the debt contract without granular information. By charging the highest rate $R^f(\bar{a})$ (but letting all borrowers default), those fintech customers repay βa. In sum, given the bank's equilibrium strategy, information beyond $\hat{a}$ has no benefit for the fintech.

Bank equilibrium strategy and uniqueness of equilibrium Why is the bank's equilibrium strategy such that it eliminates the fintech's incentive to acquire more information? Different lending technologies is the fundamental force behind Theorem 1. Essentially, the collateralized bank lending is not subject to the winner's curse that potentially arises from the fintech's private information. The "private value" setting naturally leads to this key observation, as latent type a has no fundamental value to the bank (though, "no winner's curse for bank loans" could endogenously arise even when the bank cares a bit about a, as shown in Remark 2 and Online Appendix 7.2.) As a result, the bank only reacts to the fintech's *quote itself*, cutting its own rate when the fintech's quote is high, regardless of any information implied by this quote. This aggressive competition from the bank removes any incentive for the fintech to learn beyond $\hat{a}$.

For the uniqueness of the equilibrium, first, any equilibrium information structure must be two intervals. In another potential equilibrium with a finer information structure, bank's strategy which only reacts to rates per se would be still in the form of Eq. (20). (This result will be illustrated shortly in the example of a perfectly informed fintech.) Hence, a finer information structure cannot be supported because the fintech prefers a less costly two-interval structure that achieves the same lending profits. Second, with the desirable curvature properties of information cost (Assumption 3), the first order condition (22) corresponds to a unique equilibrium screening threshold $\hat{a}$.

Remark 2. We clarify that the single-threshold result does not rely on the private value setting. First, the case that the fintech could enforce a smaller collateral value (relative to the bank, say θ) is easier, as it is equivalent to a level shift in the productivity a to $a + \theta$ of

[16] It is possible that $\underline{r} > R^f(a)$, so that the first region $\tilde{r}^f \quad [R^f(a), R^b]$ covers the entire equilibrium domain of the rates offered by the fintech.

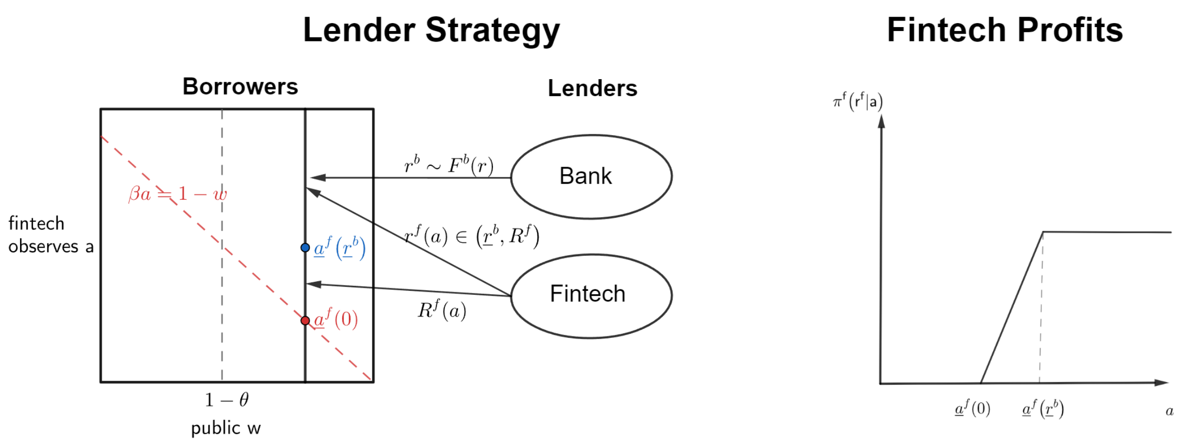


Figure 4: Fintech Perfectly Observes a

all borrowers. Second, suppose that the bank's enforcement technology is $\Phi^b(a) = \theta + \gamma a$ for some small $\gamma > 0$. The single-threshold information structure still arises in equilibrium. As the key feature of my model, physical collateral protects the bank from losses when lending to borrowers with *low productivity a*, i.e., the bank suffers no winner's curse from borrowers (with $a < \hat{a}$) rejected by the privately informed fintech. In fact, because the bank extracts all the surplus from these captured borrowers, I show the resulting upper bound interest rate is $\Phi^b(\hat{a}) = \theta + \gamma\hat{a}$. This implies that, when competing for borrowers with $a \geq \hat{a}$, bank loans are *endogenously riskless* as bank interest rates are always offered below the upper bound $\Phi^b(\hat{a})$. Therefore, the resulting competition equilibrium has the same structure as that in the private value setting with $\gamma = 0$. As shown in Online Appendix 7.2, when $\gamma \to 0^+$, the equilibrium threshold $\hat{a}$ is independent of γ; in fact, the equilibrium differs from that in Theorem 1 only in terms of pricing, due to the bank's better enforcement and rent extraction.

The case of perfect information This example further illustrates the fintech's learning incentives. Imagine that the fintech is endowed with perfect information (or "free" learning). The left panel of Figure 4 illustrates the fintech's perfectly customized lending strategy in equilibrium (Online Appendix 7.3 fully characterizes the equilibrium): the fintech rejects unprofitable borrowers with $\beta a < 1 - w$, and uses a pure strategy $r^f(a)$ to perfectly customize rates to remaining borrowers.

With the fintech's pure strategy, the bank infers the type of the marginal customer from competition, but all types have the same collateral value. In fact, the bank's equilibrium strategy is

$$F^b(r) = 1 - \frac{\underline{r}^b}{r}, \text{ with } \underline{r}^b = \frac{G(\hat{a}) R^b}{G(\hat{a}) + 1 - G(\underline{a}^f(\underline{r}^b))},$$

which is exactly the bank strategy in Theorem 1 with $c \to 0$ where the fintech learns about the cutoff $\hat{a}$ only. Hence, the bank only reacts to the fintech's screening cutoff $\hat{a}$, which reflects the size of the bank's captured borrowers.[17]

Hence, another equilibrium exists for $c = 0$, besides the one given in Theorem 1 for $c \to 0$. Because even perfect information brings no benefit beyond the threshold, the single-threshold structure becomes the unique equilibrium as long as information is costly.

3.3 Fintech as Providing Different Lending Services

I now discuss key implications of the model, and contrast them with those from canonical credit competition models.

3.3.1 Why is information acquisition unsecured lending so coarse?

In canonical credit competition models with a "common value" setting, lenders have incentive to acquire more information in order to gain strategic advantage and information monopoly. For instance, a higher signal precision (of a binary signal, e.g., Hauswald and Marquez, 2003; He, Huang, and Zhou, 2023) improves lending decision, and finer information helps the informed lender customize his bid (Milgrom and Weber, 1982; Riordan, 1993; He, Huang, and Parlatore, 2023). Importantly, competitors are concerned about the winner's curse, and respond by bidding less aggressively.

This acute theoretical force poses some empirical regularities in the banking industry as a puzzle. For instance, fintech and bigtechs tend to use coarse categories in their internal ratings (e.g., Vallee and Zeng, 2019). Additionally, observations in the unsecured lending business suggest that sophisticated lenders are using fairly unsophisticated lending strategies. For example, credit card lenders with access to rich data, such as in-house transaction histories, offer the same interest rate to customers, even when they have significantly different observable characteristics.

My theory offers some fresh insight in understanding the "coarseness" of the lending

[17] As illustrated in the right panel of Figure 4, this leads to a constant rent for the fintech when there is bank competition, i.e., $a \geq \underline{a}^f(\underline{r}^b)$, despite its perfectly customized offers. Borrowers with $ain[\hat{a} = \underline{a}^f(0), \underline{a}^f(\underline{r}^b))$ always choose the fintech offer $R^f(a)$, which is less expensive than the lowest bank quote $\underline{r}^b$. However, the fintech can still extract the same surplus βa without customization by issuing risky loans that charge $\underline{r}^b$.

practice. Even if information is free, unsecured lending does not customize its offers based on information, because competition from the secured lending option eliminates information rent. Furthermore, my model suggests that tailored pricing only arises in less competitive environments. A testable implication is that unsecured lending should be coarse at the loan origination stage when competing offers are more common; but once the loan is taken, the lender gains a monopolistic power, and we should observe sophisticated and customer-tailored pricing (via fees).

3.3.2 Specialization and competition

Fintech lending provides a new way to deal with limited enforcement and channel funds to households and small businesses. The credit market outcome features specialization and nuanced implications from technological improvements.

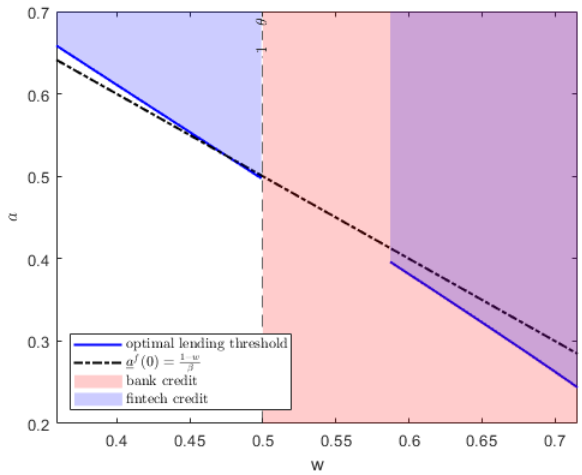
Landscape of lending Recall that the model features a two-dimensional setting for characterizing the entire landscape of borrowers, where w represents the observable credit quality and a the latent credit quality. Due to different lending technologies, the bank and the fintech are each better at serving customers with certain characteristics. The traditional bank grants credit based on observable qualities such as LTV ($w \geq 1 - \theta$ in my model). Thanks to the front-end service, the fintech's new enforcement technology suits borrowers with high latent qualities, who are selected via information acquisition. The next proposition studies the fintech's optimal lending standard as a function of w.

Proposition 1. *The fintech does not acquire information in mid-ranged w. In addition, the screening threshold is decreasing in wealth, i.e., $\frac{\partial \hat{a}(w)}{\partial w} < 0$.*

Proof. See Appendix 6.2. □

Figure 5 illustrates the landscape of credit access with shaded areas. As shown, the fintech only makes an offer to borrowers above the blue solid line $\hat{a}(w)$, which is downward-sloping as borrowers with high w (low LTV) are less risky. These high-productivity borrowers are granted another option by the new lending technology: the previously unbanked become financially included, and wealthy borrowers already with bank credit access enjoy lower interest rate from competition. My paper thus highlights further specialization in customers based on the latent quality, while under canonical common-value setting, screening is correlated across lenders to select the high latent qualities that lenders care about equally.

Figure 5: Screening Threshold and Landscape of Lending



The solid blue line is the equilibrium screening threshold $\hat{a}$. Information cost results in the gap between $\hat{a}$ and the zero-NPV borrower $\underline{a}^f(0)$ (black dot-dashed line), as well as no information acquisition in mid-ranged w. The shaded areas illustrate access to credit: borrowers in red (blue), i.e., $w \geq 1 - \theta$ ($a \geq \hat{a}$), have access to bank (fintech) credit; both bank and fintech compete in the north-east corner (purple).

The competition environment for the fintech varies across the markets $w \geq 1 - \theta$ that are already with bank credit. In wealthy markets, where borrower surplus is high, the fintech can effectively compete for customers who were previously squeezed by the bank. However, in markets with mid-ranged w, even the bank faces tight margins. Hence, the fintech finds it challenging to compete due to information costs, so it scales back and exits these markets.[18] As shown in Proposition 1 and Figure 5, fintech lending thrives in both unbanked and wealthy population as a result of financial inclusion and competition for rent.

The model prediction is consistent with empirical findings, when mapping w as observable and a as latent credit quality. For example, in Di Maggio, Ratnadiwakara, and Carmichael (2021) the fintech lender (Upstart) generates profits from both unbanked low-FICO customers and from high-FICO customers. Additionally, in line with specialization in latent quality a, the fintech picks up the "invisible primes" from low-FICO borrowers (in my model, borrowers with $a \geq \hat{a}$ and $w < 1 - \theta$), while in the high-FICO segment some are only selected by the bank model rather than the fintech model (in my model, $a < \hat{a}$ so rejected by the fintech).

[18] Section 4.1 characterizes the credit competition equilibrium when the fintech is uninformed. Depending on primitive values, in some of the mid-ranged markets where the fintech does not acquire information, it may still be present; nevertheless, it would not make any profit.

Improvement in lending technologies With the advent of new technologies (e.g., mobile internet, big data, and machine learning), it is often argued that fintechs and bigtechs might bring disruption to the entire financial industry. This part analyzes the implications of fintech expansion as its technologies improve. Along this dimension, my model has some unique implications that contrast with those of canonical credit competition models.

Under the canonical setting (Hauswald and Marquez, 2003; He, Huang, and Zhou, 2023), the fintech is one of the privately informed lenders, and its new technology is about acquiring better information more efficiently. Hence, the fintech becomes the strong player and hurts traditional lending. In contrast, my model highlights that the fintech's lending technology involves both "enforcement" and "information acquisition;" the detailed technology matters for the implication on the incumbent traditional banking. As shown formally by the next proposition, when the "information acquisition" technology improves, the traditional lending may actually benefit as a result.

Proposition 2. *In markets $w \geq \hat{w} > 1 - \theta$ where the fintech acquires information,*

1. *as the enforcement technology improves, the fintech lowers screening threshold $\hat{a}$ and bank profits decrease, i.e.,*

$$\frac{\partial \hat{a}}{\partial \beta} < 0, \ \frac{\partial \pi^b \left(r^b; w\right)}{\partial \beta} < 0;$$

2. *as the information acquisition technology improves, under Assumption 1, the fintech increases screening threshold $\hat{a}$ and bank profits increase, i.e.,*

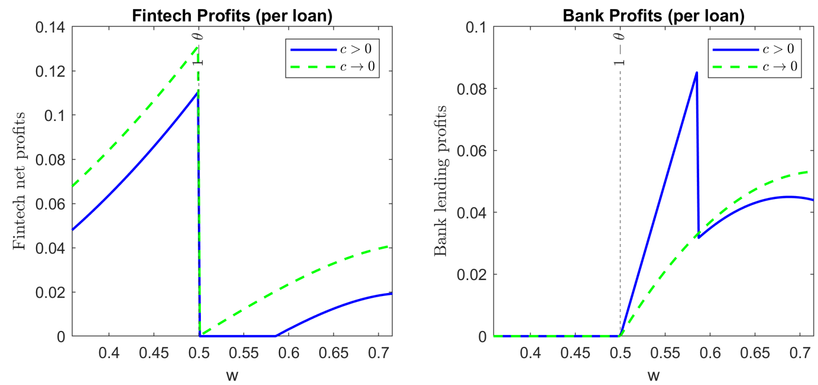
$$\frac{\partial \hat{a}}{\partial c} > 0, \ \frac{\partial \pi^b \left(r^b; w\right)}{\partial c} < 0.$$

Proof. See Appendix 6.3. □

When improvement is about enforcement (higher β), more customers become suitable for fintech lending. In equilibrium, the fintech lowers the screening threshold $\hat{a}$ and competes for more borrowers, thus hurting bank profits. Intuitively, different lending services are essentially about different ways to enforce repayment; a smaller enforcement friction therefore reduces differentiation and intensifies competition. From this perspective, the impact of fintech technology improvement on competitor bank is similar as in canonical models.[19]

[19] Whether technology improvement benefits the fintech itself is ambiguous, because a stronger fintech may invite more aggressive competition from the bank.

Figure 6: Lender Profits and Information Costs



Profits are are adjusted for loan-size for comparison across w. The blue solid line (green dashed line) illustrates profits when information cost $c > 0$ ($c \to 0$).

In sharp contrast, improvement in information technology (a smaller c) increases the competitor bank's profits. As shown in the right panel of Figure 6, in markets where the fintech acquires information ($w > 0.6$), bank profits increase (from blue solid line to green dashed line) as the information cost $c > 0$ further reduces to near zero $c \to 0$.

The intuition behind this intriguing result is that costly information acquisition leads to lax screening relative to the frictionless benchmark. The markets where lenders compete are those with relatively high w, implying that the population is generally of lower risk for the fintech (the medium borrower is positive NPV under Assumption 1.) As the lemon problem is not severe, information costs lead to lax screening which teases out the more easily identified "extreme lemons," but still serves some ineligible borrowers. Now, suppose that the information becomes less expensive to acquire. The fintech is able to identify and exclude some previously served lemons, so it competes for fewer customers and has a more focused lending. This actually benefits the traditional bank which views all borrowers as good quality because of collateral. Lending service differentiation plays a key role in this mechanism, as the fintech's better information acquisition technology helps it pick more suitable (not necessarily better from the traditional bank's view) customers to serve.

In summary, Proposition 2 highlights that the new fintech lender offers a different lending service. Better enforcement technology enlarges the set of borrowers who get a "second chance" and increases competition. Better information technology leads to a more efficient separation of borrowers into the different lending services, and may even benefit the traditional banking sector.

Long term co-existence The competition with the new fintech/bigtech lending sheds light on how the traditional banking sector will respond over the long run. As the fintech provides a different lending service, it would not eliminate the rent of traditional lending as canonical models predict. In fact, both lenders earn positive profits in my model, while under the canonical setting, the old fashioned lending who is falling behind the new information technology would make zero profits (Hauswald and Marquez, 2003). In addition, the new lending often relies on front-end services (platforms, payment or others) for enforcement and platform data. For traditional banking to also develop the lending technology, it would need to build certain platform infrastructure altogether, besides investing in information processing (IT equipment, software, algorithms) as predicted in canonical models (He, Jiang, Xu, and Yin, 2022). Hence, my paper predicts that the traditional sector has less incentive to aggressively fight back; if they do, acquiring the fintech entrants seems a more efficient route. In sum, different lending services could coexist and compete in the long run, each better at serving certain customers.

4 Information Technology and Fintech Expansion

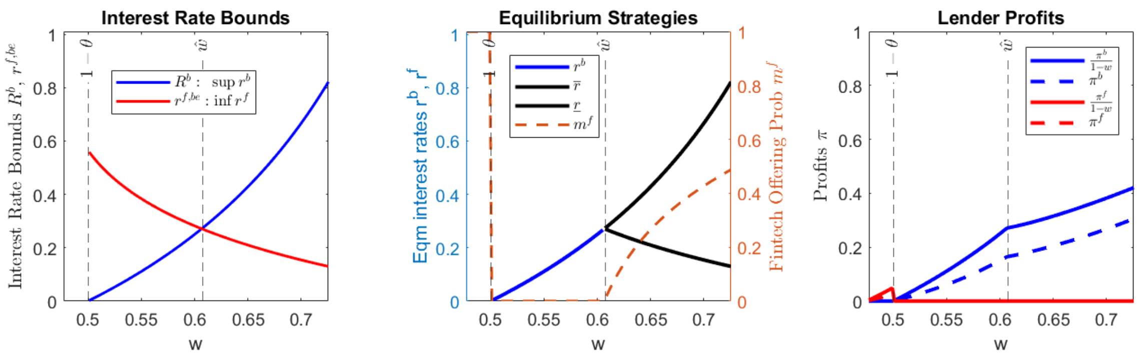
The information technology is essential for the fintech's expansion in the lending business. Starting with Section 4.1, we use a benchmark case of uninformed fintech to show that, in the absence of affordable information, the fintech can only generate profits in the unbanked population by issuing risky loans. Earlier discussion in Section 3 shows how fintech lending prospers via screening out ineligible borrowers, but this resolution requires low learning cost which only happens gradually with technology advancement and data accumulation.

By enabling cross-market predictability, the big data technology significantly speeds up the process. The fintech industry's expansion to wealthy markets can be an endogenous outcome of the early-stage lending in the unbanked population, where fintech companies extrapolate their learnings by developing predictative algorithms. My model thus provides insights into the fintech's fast expansion in the past decade.

4.1 No Information Benchmark and Implication on Expansion

To demonstrate why information technology is essential for the fintech, I consider the benchmark case where the fintech is uninformed due to infinitely high information cost $\mathtt{c} = \infty$. This benchmark reflects the early stage of the digital lending industry, when data is still not

Figure 7: Benchmark of No Information Acquisition



The left panel draws $r^{f,be}$ and R^b and the fintech exits when $r^{f,be} > R^b$. In the middle panel, the dashed line illustrates fintech participation m^f (the probability of making an offer); the solid lines are equilibrium interest rates, and mixed strategy equilibrium the bounds $\underline{r}$ and $\overline{r}$ of randomized rates (black lines) are provided. The right panel shows the resulting lending profits.

sufficient for effective information processing.

Suppose $w \geq 1-\theta$; would the fintech lender enter the market? Define $r^{f,be}$ to be the fintech's break-even interest rate (as if it is the only lender) to cover the loan cost:

$$\mathsf{E}\left[\min\left\{R^f(a), r^{f,be}\right\}\right] = 0. \tag{24}$$

Here, $R^f(a) \equiv \frac{\beta a}{1-w} - 1$ is the maximum interest rate payment from borrower (w, a) to the fintech. Recall that $R^b \equiv \frac{\theta}{1-w} - 1$ is the highest interest rate that a riskless bank loan can charge. Therefore, the fintech exits the markets where $r^{f,be} > R^b$ because it could only attract low-quality borrowers who default and pay back less than R^b.

Proposition 3. *Suppose $c = \infty$. In the unique credit market equilibrium, the fintech makes zero profits when the bank is present, i.e., $\pi^f(w) = 0$ if $w \geq 1-\theta$. Moreover,*

1. *when $1-\theta \leq w \leq \hat{w}$ where $\hat{w}$ satisfies $r^{f,be}(\hat{w}) = R^b(\hat{w})$, the fintech lender exits;*

2. *when $w > \hat{w}$, the fintech randomly makes an o er.*

Proof. See Online Appendix 7.4 for proof and equilibrium characterization. □

During the early stages, the fintech without rich platform data only relies on the publicly available credit quality information (i.e., w in the model). Proposition 3 and the right panel of Figure 7 show that the fintech can only make profits in the unbanked population.

In markets with banked population but relatively low w, as shown in the left panel of Figure 7 for $1-\theta \leq w \leq \hat{w}$, the fintech's required default premium $r^{f,be}$ sits above the maximum bank rate R^b. Because the competing bank is aggressive due to its own tight margins, the fintech chooses to exit under such circumstances.

Even when $w > \hat{w}$ (equivalently $r^{f,be} < R^b$) so that there is room for fintech entry, the adverse selection puts it at a disadvantage when competing against the riskless bank lending. A mixed strategy equilibrium arises. When the bank undercuts its offer to $r^{f,be}$ as in Bertrand, the fintech *makes a loss* and exits; but this then prompts the bank to increase its rate, inviting fintech entry. In equilibrium, as shown in the middle panel of Figure 7, the fintech randomly makes an offer ($m^f < 1$) and earns zero profits; the common bounds of the lenders' randomized quotes, $r^{f,be}$ and R^b, reflect competition as well as the bank's incentive to squeeze its captured customers (when the fintech randomly withdraws.)

A comparison with the results in Section 3 (for instance, the left panel of Figure 6 versus the right panel of Figure 7) emphasizes the importance of information acquisition in establishing fintech lending in wealthy markets. Although an uninformed fintech occasionally makes loans in these markets, the fintech lender only makes profits here when it actively acquires information to effectively screen out ineligible borrowers (Section 3). This could be achieved gradually over time as more data is accumulated via "trial and error" and the information cost decreases.

However, this resolution is costly and takes time, because the fintech must accumulate data and establish effective screening independently for each specific market through trial and error, since information is *not transferable* across different markets. Expanding into wealthy markets is particularly challenging, because early-stage profitable fintech businesses are in the unbanked population. A lot of data accumulated from early stage may not be useful for expanding into wealthy borrowers, so the fintech has to start from scratch.

The advent of big data technology has significantly reduced information costs by enabling out-of-sample predictability. The data collected from the fintech's early-stage operations in unbanked markets can be used to develop predictive algorithms for identifying potential customers in wealthy markets, as some latent traits are correlated between even observably heterogeneous groups. Overall, big data technology has played a key role in the fast expansion of fintech lending in the past decade.

4.2 Big Data: Out-of-Sample Forecasts via Latent Traits

As explained, prior to the emergence of big data technology, it was challenging to generate large-scale forecasts based on latent traits. Soft information collection was heavily reliant on loan officers to engage with borrowers, leading to high information acquisition costs. Besides the issue of human capacity, the soft information assessed by humans *is not transferable*, which meant that data had to be collected independently for each market. As a result, expansion to new markets is difficult.

Big data technology significantly enriches the data source and allows for the "hardening" of information about latent characteristics. In the case of fintech lending, its unique digital ways of interacting with customers facilitates alternative data accumulation. More relevant to my study, big data technology allows for out-of-sample forecasting. For instance, if a food truck business is found to be productive and its location footprints are incorporated into the algorithm as a predictive factor, then the algorithm can identify food trucks with similar location footprints and favorably predict their productivity, even when the truck owners differ in observables such as leverage and credit scores.

My model could capture this crucial feature of out-of-sample predictability, once we set the latent quality a to be correlated across observably different borrowers indexed by w. In this extension, acquiring an information structure P^w means that the fintech has established an algorithmic model in some market w for identifying the categorical traits in P^w. This algorithm could be used to assess another market $w \; = w$ to classify borrowers into the same latent trait categories.

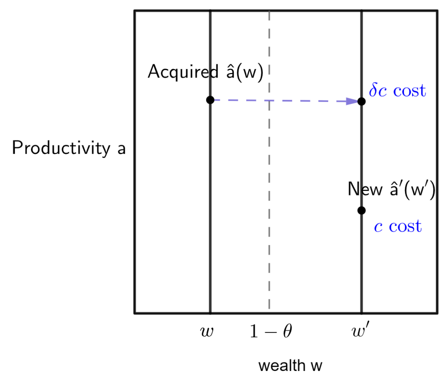
Formally, recall that the information cost of establishing an algorithm is $c \cdot I\left(P^w\right) dw$. When applying an established algorithm to another market $w \; = w$, i.e., $P^w \; = P^w$, I assume that the information cost is reduced to $\delta c \cdot I\left(P^w\right) dw$ with $\delta \quad (0, 1)$. This means that the fintech pays a cost in collecting the data of new customers, but the algorithm systematically categorizes customers into P^w, at a much lower cost than in the first market w. If the fintech decides to acquire *new information* $P^w \; = P^w$, then the unit information cost is still c. In sum, the fintech's superior cross-market forecasting is captured by the following information cost, with $\delta = 1$ nests the case studied in Section 3:

$$C\left(P^w\right) = \begin{cases} \delta c I\left(P^w\right) dw, & \text{if } P^w \; = P^w, \\ c I\left(P^w\right) dw, & \text{if } P^w \; = P^w. \end{cases} \tag{25}$$

4.3 Fintech Expansion

The big data technology enables cross-market forecasting and so markets are no longer independent. Solving for the credit market equilibrium becomes highly complex, but the path-independent entropy information acquisition cost allows me to solve the equilibrium via a

Figure 8: Big Data Technology: Cross-Market Forecasting



static problem (where the forward-looking fintech takes into account its future predictability on other markets). To be more specific, the fintech jointly chooses an information structure profile $\{P^w\}_{w \in [0,\overline{w}]}$ for all markets to maximize the total net profits, with the cross-market information spillovers in Eq. (25).

The analysis of this challenging problem will focus on some key properties related to the paper's theme on different lending, while leaving the full-blown characterization for future research. To this end, I first present a proposition stating that the fintech still adopts single-threshold in each market, which echoes the limited value of information under the "private value" setting. Then, I provide an example to illustrate how the big data technology significantly reduces information costs and helps the fintech expand into new markets.

Proposition 4. *The equilibrium information structure profile $\{P^w\}$ is a decreasing step function $\hat{a}(w)$ defined over the markets where the fintech acquires information. Specifically, there exists a sequence of cutoffs $\hat{a}_1 > \hat{a}_2 > \cdots > \hat{a}_n$ for $w_1 < w_2 < \cdots < w_n$, so that*

1. *in markets $w_i \leq w < w_{i+1}$, the information structure is a single-threshold partition*

$$P^w = \{[\underline{a}, \hat{a}_i), [\hat{a}_i, \overline{a}]\},$$

and the fintech rejects borrowers of $a < \hat{a}_i$;

2. *in each threshold market $w_i \in \{w_1, w_2, \cdots, w_n\}$, the fintech is indifferent between adopting $\hat{a}_{i-1}$ and $\hat{a}_i$ as the screening threshold.*

Proof. See Online Appendix 7.5. □

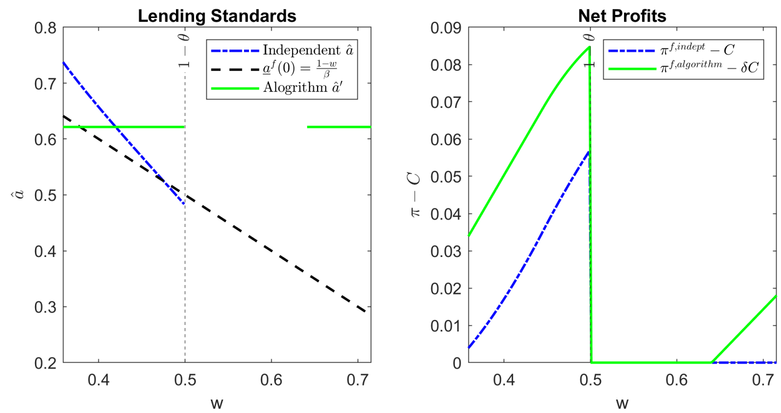
The result in Proposition 4 could be explained by three points. First, the number of algorithmic models or information structures used by the fintech is finite for the entire range of markets, because it typically uses the same algorithm in neighboring markets. In neighboring markets, acquiring new information only slightly improves screening due to continuity, while the costs of doing so are much higher than those of applying established algorithms. Second, echoing the main take-away from Theorem 1, the fintech focuses on the single-threshold partition structure within each market. This is because customizing interest rates is useless when competing against traditional secured lending, and the purpose of information is to screen out risky loans. Last, as w increases, there are fewer lemons, and the fintech has an incentive to lower the screening standard, resulting in decreasing $\hat{a}(w)$. Taken together, the equilibrium information strategy is to only lower $\hat{a}$ at critical markets $\{w_i\}$ to improve screening.

Proposition 4 thus simplifies the information acquisition problem to finding both the algorithms indexed by screening standards $\{\hat{a}_i\}$ and the critical markets $\{w_i\}$ where it is optimal to lower the screening threshold (from $\hat{a}_{i-1}$ to $\hat{a}_i$). This simplified problem is illustrated in Figure 8: suppose that a relatively high screening standard $\hat{a}(w)$ is used in market w; in another market $w > w$ with less risky customers, the fintech chooses between applying the same algorithm $\hat{a}(w)$, which has a smaller unit information cost δc but maintains a high screening standard, and lowering the screening standard to $\hat{a}(w)$ but incurring a higher information cost c.

Using a numerical example, I illustrate how big data technology enables the fintech to expand beyond unbanked markets by allowing for cross-market forecasting. The results are shown in Figure 9, where the blue dash-dotted line represents the case of independently acquiring information across markets (i.e., $\delta = 1$), while the green solid line represents the case of allowing for cross-market predictability (i.e., $\delta < 1$). In the latter case, the fintech is assumed to use the same algorithm for all potential markets for simplicity, which gives a lower bound of its net profits.

In the case where information must be independently acquired for each market, as discussed in Section 3, the blue dash-dotted line shows that the fintech chooses not to acquire information when $w \geq 1 - \theta$ (left panel). Consequently, it only makes profits in the unbanked population (right panel). In contrast, big data technology significantly reduces total information cost and enables expansion to wealthy markets. As shown in the green solid line, the fintech can establish an algorithm from the unbanked markets to identify high productivity types ($a \geq \hat{a}$). The algorithm is then used to forecast wealthy markets $w > 0.65$, allowing

Figure 9: Fintech Expansion



Screening threshold (left) and lender profits (right). Without cross-market predictability (blue dash-dotted line), the fintech could only make profits in unbanked area. With big data and cross-market predictability (green solid line), the fintech expands into wealthy markets and makes profits there by applying the algorithm established from unbanked population.

the fintech to compete for high types only (left panel), so the fintech can generate profits in both unbanked and wealthy populations (right panel).

Furthermore, with the expansion facilitated by the algorithmic models, the fintech can position itself as a more specialized and less aggressive competitor to the traditional banking sector, because fintech lending is influenced by algorithms developed from unbanked markets. In these markets, a high lending standard is used to pick up the "invisible primes," and when leveraging this information for other markets, fintech screening may be tilted towards this cherry-picking standard. Hence, the fintech competes for fewer customers, which can lead to higher profits for both lenders, as compared with the case where the fintech acquires information independently for each market. Di Maggio, Ratnadiwakara, and Carmichael (2021) provides empirical support for this "invisible prime" strategy of fintech lending, where the fintech model is still more selective than the traditional bank's model in markets of high FICO score borrowers, suggesting out-of-sample predictability.

In practice, with capital layout frictions, the fintech's entry into different markets occurs sequentially, first targeting underserved markets where it can establish itself and build a profitable business model before expanding to more competitive markets. To speak to this concern, an example in Online Appendix 7.5 considers the expansion of a fintech lender with the "history" of operating in low-w markets with a high lending standard. I leave the full-blown analysis of such dynamics for future research.

5 Conclusion

Fintech lending has disrupted traditional banking with fast, flexible services and innovative screening, especially in weaker banking markets like Asia and Africa. Although its development has been slower in stronger markets like the U.S. and Europe, the competition landscape could change with the entry of bigtech companies like Amazon and Apple into lending. Another disruptive force is the rise of payment companies like Square and Stripe in response to the U.S.'s historically slow and expensive payment system, and they easily expand into lending with the abundance of customer data and front-end enforcement.

My research highlights the different lending provided by fintechs. Breakthroughs in information technologies enable fintechs to mitigate the adverse selection differently from the traditional lending, and the competition between these different lending exactly eliminates any rent from information-based customization for the fintech. Contrary to conventional wisdom, information acquisition would be coarse. In the long run, a coexisting system would be more likely, with each type of lending better at serving certain borrowers.

Open questions remain about alternative lending. For example, most fintech lenders are not depository institutions and face funding side limitations, and this restrict their ability to offer, say credit lines or large-sized loans that are areas where banks have their unique role (Kashyap, Rajan, and Stein, 2002). Given these funding limitations and the fintechs' front-end convenience and information technology, it would be interesting to study potential collaborations between banks and fintechs in a non-competitive setting (Hu and Zryumov, 2022), which is already supported by recent evidence (Jiang, 2019; Beaumont, Tang, and Vansteenberghe, 2022).

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6 Technical Appendix

6.1 Proof of Theorem 1

Lemma 1. *The Shannon entropy of a partition $P \equiv \{A^i\}$ of a random variable $a \in A$ with pdf $g(a)$ can be computed using the following formula:*

$$I(P) = -\sum_{A^i \in P} \left[\mathrm{P}\left(A^i\right) \log \mathrm{P}\left(A^i\right) \right].$$

This is equivalent to the entropy of the categorical distribution that indicates event realizations.

Proof. Applying the definition of entropy as the distance between the prior belief and the posterior belief to the partition P,

$$I(P) \equiv -\mathsf{E}[\log g(a)] + \mathsf{E}\left[\mathsf{E}\log g\left(a \middle| A^i\right)\right],$$

where $g(a|A^i)$ is the conditional probability density function,

$$g\left(a \middle| A^i\right) \equiv \begin{cases} \frac{g(a)}{\mathsf{P}(A^i)}, & \text{if } a \in A^i, \\ 0, & \text{if } a \notin A^i. \end{cases}$$

Then we can derive the expression for $I(P)$ as follows:

$$\begin{aligned} I(P) &= -\int_A g(a)\log g(a)\,da + \sum_{A^i \in P} \mathsf{P}\left(A^i\right)\left[\int \mathbf{1}_{a \in A^i}\frac{g(a)}{\mathsf{P}(A^i)}\log\frac{g(a)}{\mathsf{P}(A^i)}da\right] \\ &= -\sum_{A^i \in P}\int \mathbf{1}_{a \in A^i} g(a)\log g(a)\,da + \sum_{A^i \in P}\int \mathbf{1}_{a \in A^i} g(a)\left[\log g(a) - \log \mathsf{P}\left(A^i\right)\right]da \\ &= \sum_{A^i \in P}\int \mathbf{1}_{a \in A^i} g(a)\left[-\log \mathsf{P}\left(A^i\right)\right]da \\ &= -\sum_{A^i \in P}\left[\mathsf{P}\left(A^i\right)\log \mathsf{P}\left(A^i\right)\right]. \end{aligned}$$

The expression for $I(P)$ is equivalent to the entropy of the categorical distribution with random variable X that indicates event realization—$X = A^i$ with probability $\mathsf{P}(A_i)$, whose entropy is

$$I(X) \equiv -\mathsf{E}[\log \mathsf{P}(X)] = -\sum_{A^i \in P}\left[\mathsf{P}\left(A^i\right)\log \mathsf{P}\left(A^i\right)\right].$$

□

6.1.1 The case of $w < 1 - \theta$

Lemma 2. *If $w < 1 - \theta$, the fintech only acquires information about a single threshold $\hat{a}$ (if it acquires information), resulting in $P = \{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\}$, where $\hat{a}$ satisfies*

$$\underbrace{(1-w)\,h(w)\,R^f(\hat{a})}_{\text{marginal borrower return}} = \underbrace{c\log\left(\frac{G(\hat{a})}{1-G(\hat{a})}\right)}_{\text{marginal info cost}}.$$

Proof. First, the monopolist fintech only considers two binary actions: either offering interest rate $R^f(\overline{a}) \equiv \frac{\beta\overline{a}}{1-w} - 1$ or rejecting the borrower. To see this, conditional on making an offer, quoting $R^f(\overline{a})$ generates the highest profits among any potential quote r^f regardless of borrower type a, because $\min\left\{R^f(\overline{a}), R^f(a)\right\} \geq R^f(a) \geq \min\left\{r^f, R^f(a)\right\}$. However, if the expected profit when offering $R^f(\overline{a})$ is negative, the fintech will reject the borrower.

Second, the fintech acquires information regarding a single threshold $\hat{a}$. Given binary actions, the fintech only differentiates at most two events, which I call A^{rej} upon which it rejects the borrower and A^{offer} upon which it offers $R^f(\overline{a})$. Furthermore, I argue that A^{rej} and A^{offer} must be convex. Suppose not, and then there exist two subsets $\mathbf{a^{rej}}, \mathbf{a^{offer}}$ of equal measure such that

$$\sup \mathbf{a^{offer}} < \inf \mathbf{a^{rej}} \quad \text{where} \quad \mathbf{a^{rej}} \quad A^{rej}, \quad \mathbf{a^{offer}} \quad A^{offer}, \quad \text{and} \quad \mathsf{P}\left(\mathbf{a^{rej}}\right) = \mathsf{P}\left(\mathbf{a^{offer}}\right)$$

Then we can construct a new partition

$$\left\{\hat{A}^{rej} \equiv A^{rej} \quad \mathbf{a^{offer}} \setminus \mathbf{a^{rej}}, \hat{A}^{offer} \equiv A^{offer} \quad \mathbf{a^{rej}} \setminus \mathbf{a^{offer}}\right\},$$

and the fintech rejects the borrower upon $\hat{A}^{rej}$ and offers $R^f(\overline{a})$ upon $\hat{A}^{offer}$. This new strategy leads to a higher lending profits as compared with those based on $\left\{A^{rej}, A^{offer}\right\}$:

$$\underbrace{\int_{\mathbf{a^{rej}}} \min\left\{R^f(a), R^f(\overline{a})\right\} g(a)\, da}_{\mathbf{a^{rej}} \quad \hat{A}^{offer},\ \text{offer } R^f(\overline{a})} + \underbrace{\int_{\mathbf{a^{offer}}} 0 \cdot g(a)\, da}_{\mathbf{a^{offer}} \quad \hat{A}^{rej}, \text{reject}}$$
$$> \underbrace{\int_{\mathbf{a^{rej}}} 0 \cdot g(a)\, da}_{\mathbf{a^{rej}} \quad A^{rej}, \text{reject}} + \underbrace{\int_{\mathbf{a^{offer}}} \min\left\{R^f(a), R^f(\overline{a})\right\} g(a)\, da}_{\mathbf{a^{offer}} \quad A^{offer},\ \text{offer } R^f(\overline{a})}.$$

The inequality follows from $\sup \mathbf{a^{offer}} < \inf \mathbf{a^{rej}}$. In addition, both partitions share the same information cost, because $\mathsf{P}\left(\hat{A}^{rej}\right) = \mathsf{P}\left(A^{rej}\right)$ which is from $\mathsf{P}\left(\mathbf{a^{rej}}\right) = \mathsf{P}\left(\mathbf{a^{offer}}\right)$. This contradicts with the fintech's optimal choice. Hence, the partition is characterized by a single threshold $\hat{a}$,

$$P = \{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\};$$

the fintech rejects the borrower upon upon $a < \hat{a}$, and makes an offer at $R^f(\overline{a})$ otherwise.

Third, the optimal cutoff $\hat{a}$ is chosen to maximize the expected net profits:

$$\mathsf{E}\left[\pi^f\left(r^f\left(A^i\right)\middle| A^i\right)\right] - cI(P)\, dw$$
$$(1-w)\, h(w) \int_{\hat{a}}^{\overline{a}} R^f(a)\, dG(a) + c\left[G(\hat{a}) \log G(\hat{a}) + (1-G(\hat{a})) \log(1-G(\hat{a}))\right]$$

The first-order condition (FOC) with respect to $\hat{a}$ yields

$$g(\hat{a})\left[-(1-w)\, h(w)\, R^f(\hat{a}) + c \log \frac{G(\hat{a})}{1-G(\hat{a})}\right] = 0, \tag{26}$$

which requires the loss from rejecting the marginal type $-(1-w)\, h(w)\, R^f(\hat{a})$ to equal the marginal cost of information $-c \log \frac{G(\hat{a})}{1-G(\hat{a})}$. Note that the marginal cost of information at end points

$$-c \log \frac{G(\hat{a})}{1-G(\hat{a})}\bigg|_{\hat{a} \to \underline{a}} = +\infty, \quad -c \log \frac{G(\hat{a})}{1-G(\hat{a})}\bigg|_{\hat{a} \to \overline{a}} = -\infty.$$

Then by continuity, there exists at least one solution to the FOC which is a local minimum. When c is sufficiently small, more solutions arise, and under Assumption 3, one can show that there are at most three solutions: two local minimum points—$\hat{a}_1$ near $\underline{a}$ and $\hat{a}_3$ near $\overline{a}$, and a unique local maximum point $\hat{a}_2$ between $\hat{a}_1$ and $\hat{a}_3$.

Moreover, the endpoints $\hat{a} = \underline{a}, \overline{a}$ correspond to the case of no information acquisition. So if the information cost is sufficiently low, the fintech must be better off acquiring information, under which the unique local maximum $\hat{a}_2$ is globally optimal. □

6.1.2 Preparation Lemmas when $w \geq 1 - \theta$

Lemma 3. *Equilibrium is in mixed strategy.*

Proof. Suppose for contradiction that equilibrium is in pure strategies: The bank offers $r^b \geq 0$, and then in response to the bank's pure strategy, the fintech must use a pure strategy of $r^f = r^b -$ or reject the borrower for any event $A \quad P$.

If the fintech always rejects the borrower, it must be the case that $r^b = \overline{r}$ in equilibrium. However, in this case, the fintech has a profitable deviation to enter. Contradiction.

If the fintech offers $r^f = r^b -$ upon some events, it must be the case that $r^b = 0$, or otherwise one lender has a profitable deviation by undercutting its competitor. Given $r^b = 0$, only the negative NPV borrowers (those with $R^f(a) \equiv \frac{\beta a}{1-w} - 1 < 0$) would choose the fintech's offer, resulting in loss for fintech. Then the fintech would have a profitable deviation to reject borrowers. Contradiction. This completes the proof that the equilibrium is in mixed strategy. □

Lemma 4. *For any r on both lenders' supports, wlog there exist an event $\hat{A} \quad P$, so that around r*

1. *bank strategy $F^b(r)$ is determined by the fintech's indi erence condition given $\hat{A}$;*
2. *the competition faced by bank, $F^f(r) \equiv \sum_{A^i} \mathrm{P}(A_i) F^f(r|A_i)$, is determined by the fintech's strategy conditional on $\hat{A}$, $F^f\left(r|\hat{A}\right)$.*

Proof. Note that if for any $A \,, A \quad P$, the supports of the corresponding fintech's strategies on interest rate offering are disjoint, then the lemma holds.

Suppose the supports are not disjoint: There exist events A and A , and let R and R denote the support of strategies upon events A and A , respectively, such that $R \cap R$ has positive measure. In equilibrium, the fintech is indifferent across any quote on support, which include some $\hat{r} \quad R \cap R$ for both A and A :

$$\pi^f\left(r^f(A)\middle|A\right) = \pi^f(\hat{r}|A), \quad \pi^f\left(r^f(A)\middle|A\right) = \pi^f(\hat{r}|A).$$

There are two cases depending on whether the fintech reaches the same profits upon A and A .

In the first case, the profit is the same,

$$\pi^f\left(r^f(A)\middle|A\right) = \pi^f(\hat{r}|A) = \pi^f(\hat{r}|A) = \pi^f\left(r^f(A)\middle|A\right).$$

Then either there is a payoff-equivalent equilibrium under which the lemma holds. To construct this equilibrium, the mass of $F^f(r|A)$ on $R \cap R$ is moved to $F^f(r|A)$ such that the resulting conditional CDFs are legitimate:

$$\tilde{F}^f(r|A) \equiv \min\left\{F^f(r|A) + \mathbf{1}_{r \quad (R \cap R \;)} \cdot \frac{\mathsf{P}(A \;)}{\mathsf{P}(A)} F^f(r|A \;), 1\right\}, \tag{27}$$

$$\tilde{F}^f(r|A \;) \equiv \mathbf{1}_{r / R \cap R} \cdot F^f(r|A \;) + \mathbf{1}_{r \quad (R \cap R \;)} \cdot \left[F^f(r|A \;) - \tilde{F}^f(r|A)\right], \tag{28}$$

where "$\min\{\cdot, 1\}$" in Eq. (27) serves to cap the CDF $\tilde{F}^f(r|A)$ below 1 when adding its mass; when binding, the "$+\mathbf{1}_{r \quad (R \cap R \;)} \cdot \left[F^f(r|A \;) - \tilde{F}^f(r|A)\right]$" in Eq. (28) becomes nonzero. The adjustment results in a pay-off equivalent equilibrium: the fintech's strategies are still optimal the specific event A or A is irrelevant; bank strategy also remains optimal because the competition it faces from the fintech, $F^f(r) \equiv \sum_{A^i} \mathsf{P}(A_i) F^f(r|A_i)$ remains unchanged.

If the resulting $\tilde{F}^f(r|A) < 1$ ($\min\{\cdot, 1\}$ is slack), then the fintech's new strategy supports $\tilde{R}$ upon A and $\tilde{R}$ are disjoint,

$$\tilde{R} \equiv R \quad (R \cap R \;), \; \tilde{R} \equiv R \setminus (R \cap R \;),$$

under which the lemma holds. If $\tilde{F}^f(r|A) = 1$, then around any $\hat{r} \quad R \cap R$, i) bank strategy $F^b(\hat{r})$ is determined by the fintech's indifference condition given $\hat{A} = A$ or A; and ii) the competition faced by bank, $F^f(\hat{r}) = \mathsf{P}(A)\tilde{F}^f(\hat{r}|A) + \mathsf{P}(A \;)\tilde{F}^f(\hat{r}|A \;) = \mathsf{P}(A) + \mathsf{P}(A \;)\tilde{F}^f(\hat{r}|A \;)$ is given by the fintech's strategy conditional on $\hat{A} = A$. This completes the proof in the first case.

In the second case, the fintech has a higher profits upon say A,

$$\pi^f\left(r^f(A)\middle| A\right) = \pi^f(\hat{r}|A) > \pi^f(\hat{r}|A \;) = \pi^f\left(r^f(A \;)\middle| A \;\right).$$

Then in equilibrium it must be $F^f(r|A) = 1$ over $r \quad (R \cap R \;)$. Otherwise, the fintech has a profitable deviation by moving the mass of $F^f(r|A \;)$ on $(R \cap R \;)$ is moved to $F^f(r|A)$, which is a contradiction to equilibrium condition. With $F^f(r|A) = 1$ over $r \quad (R \cap R \;)$, by the previous argument, the lemma holds and $\hat{A} = A$ satisfy both two conditions required. This completes the proof. $\square$

Lemma 5. *The mixed strategy equilibrium is well behaved, in that lenders randomize over the common support* $\left[\underline{r}, R^b\right]$ *without interior mass points or gaps, except that only one lender has a point mass at* R^b.

Proof. One can apply the same argument in the literature (e.g., Varian, 1980), with some necessary adjustment. In the standard argument, if lender j's distribution F^j has some irregularity, then its competitor lender j must also have some irregularity as a response of maximizing profits from residual demand, given by $\max_{r \quad B(\hat{r})}[1 - F^j(r)]r$. Then at least one of them would have a deviation incentive. In my model, the profits are

$$\pi^f\left(r^f, A^i\right) \quad \underbrace{\int^{\underline{a}(r^f)}}_{\text{low } a} \mathbf{1}_{A^i} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{\text{winning prob}} \cdot \underbrace{R^f(a)}_{\text{repayment}} dG(a) + \underbrace{\int_{\underline{a}(r^f)} \mathbf{1}_{A^i} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^b\left(r^f\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^f}_{\text{repayment}}, \tag{29}$$

$$\pi^b\left(r^b\right) \quad G\left(\underline{a}^f(0)\right)\cdot r^b + \underbrace{\int_{\underline{a}(r^b)} dG(a)}_{\text{high } a}\cdot \underbrace{\left[1-F^f\left(r^b\right)\right]}_{\text{winning prob}}\cdot \underbrace{r^b}_{\text{repayment}}. \tag{30}$$

First, if the competition is being kept constant around r (due to an irregularity in competitor's strategy), a lender could strictly gain through an irregular distribution because its profit is still strictly monotone in r.[20] Second, although the fintech has private information A^i, Lemma 4 associates quotes with a specific event $\hat{A}$ that is decisive for lender strategies. As a result, the canonical arguments would apply.

Now I show the detailed proof. First, there is no interior mass point in $F^j(\cdot)$, and one lender could have a mass point at R^b. Otherwise suppose lender j has a mass point at $\hat{r} < R^b$ in equilibrium. Then in this conjectured equilibrium, $(\hat{r}, \hat{r} + \ )$ is not a subset of the other lender j 's support. Suppose not; then on any borrowers that lender j would charge $\hat{r} +$ potentially, it would strictly prefer charging $\hat{r} -$. It follows that one profitable deviation for lender j is to increase the quote at mass point to $r^j \quad (\hat{r}, \hat{r} + \ )$. Contradiction. The only exception is when the point mass is at $\hat{r} = R^b$. If both lenders have a point mass, then both have a profitable deviation by undercutting the competitor.

Second, lenders' share common upper support $\overline{r}^b = \overline{r}^f = R^b$, and wlog the same lower support $\underline{r}^f = \underline{r}^b = \underline{r}$. It is wlog to focus on $\overline{r}^f \le \overline{r}^b$. This is because when $r^f > \overline{r}^b$, the fintech's profit is a constant $\int^{\underline{a}(\overline{r}^b)} \mathbf{1}_{A^i}\left[1-F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a)$ (the first term in Eq. 29) irrelevant of r^f. If $\overline{r}^f < \overline{r}^b$, in the conjectured equilibrium, the bank with captured borrowers must put all weight of $r^b \quad \left[\overline{r}^f, \overline{r}^b\right]$ at R^b. Then the fintech has a profitable deviation by marginally increasing the interest rate $\overline{r}^f -$ to $\overline{r}^f +$ (on the corresponding borrowers). As for lower supports, if $\underline{r}^j < \underline{r}^{j}$, lender j has a profitable deviation by put all weight of $r^j \quad \left(\underline{r}^j, \underline{r}^{j}\ \right)$ at $\underline{r}^{j} -$.

Third, there is no (interior) gap. Let $(r\ , r\ )$ refer to the potential gap. Suppose the bank has a gap. Then for the borrowers that the fintech charges r , it is a profitable deviation to marginally increase the interest rate to $r\ +$ (as the demand does not change). Suppose the fintech has gap in $(r\ , r\ )$. According to Eq. (30), the bank's profit when charging $r^b \quad [r\ , r\ ]$ is $G\left(\underline{a}^f(0)\right) r^b + G\left(\underline{a}(r^b)\right)\left[1-F^f(r\ )\right] r^b$. So the bank cannot be indifferent across $[r\ , r\ ]$ and has a profitable deviation. Contradiction. □

6.1.3 Proof of Theorem 1

Proof. The case of $w < 1-\theta$ is covered in Lemma 2. When $w \ge 1-\theta$, first, I solve for for the bank strategy from the fintech's indifference condition.

For any $A^i \quad P$ upon which the fintech makes an offer with positive probability, i.e., $m^f(A^i) > 0$, let $R^i \equiv supp\left\{r^f(A^i)\right\}$ denote the support of the fintech's interest rate offering. Then for any $r \quad R^i$ which is not isolated (otherwise that point is with zero Lebesgue measure), there exists a

[20] Under Assumption 2 (conditions on $G(a)$), even though a higher r^b would lead to more low-type borrowers choosing the fintech ***and default***, the bank's revenue conditional on residual demand $\left[G\left(\underline{a}^f(0)\right) + \int_{\underline{a}(r^b)} dG(a)\right] r^b$ still increases in r^b.

sequence $\{r_n\} \quad R^i$ with $r_n \to r$, such that $\pi^f\left(r_n, A^i\right) = \pi^f\left(r, A^i\right)$, where

$$\pi^f\left(r, A^i\right) = dH(w)\left\{\int_{\underline{a}}^{\underline{a}^f(r)} \mathbf{1}_{A^i}\left[1 - F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a) + \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r)\right] r\right\}. \tag{31}$$

Applying Eq. (31) to r_n and r, we have

$$\begin{aligned}
\pi^f\left(r_n, A^i\right) - \pi^f\left(r, A^i\right) \quad & \int_{\underline{a}^f(r)}^{\underline{a}^f(r_n)} \mathbf{1}_{A^i}\left[1 - F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a) \\
& + \int_{\underline{a}^f(r_n)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r_n)\right] r_n - \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r)\right] r \\
= & \int_{\underline{a}^f(r)}^{\underline{a}^f(r_n)} \mathbf{1}_{A^i}\left[1 - F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a) + \int_{\underline{a}^f(r_n)}^{\underline{a}^f(r)} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r_n)\right] r_n \\
& + \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r_n)\right] r_n - \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \left[1 - F^b(r)\right] r \\
= & \int_{\underline{a}^f(r)}^{\underline{a}^f(r_n)} \mathbf{1}_{A^i}\left\{\left[1 - F^b\left(R^f(a)\right)\right] R^f(a) - \left[1 - F^b(r_n)\right] r_n\right\} dG(a) \\
& + \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} \cdot \left\{\left[1 - F^b(r_n)\right] r_n - \left[1 - F^b(r)\right] r\right\} dG(a).
\end{aligned}$$

As $r_n \to r$, we have $\underline{a}^f(r_n) \to \underline{a}^f(r)$ by continuity and $F^b(r_n) \to F^b(r)$ from Lemma 5. Then the first term in the above equation is of lower order than the second term (and hence) could be neglected. Applying the fintech's indifference condition $\pi^f\left(r_n, A^i\right) = \pi^f\left(r, A^i\right)$, we have

$$\int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} \cdot \left\{\left[1 - F^b(r_n)\right] r_n - \left[1 - F^b(r)\right] r\right\} dG(a) = 0,$$

which leads to

$$\left[1 - F^b(r_n)\right] r_n = \left[1 - F^b(r)\right] r.$$

The equality holds for any $r \quad R^i$ and any sequence $\{r_n\} \quad R^i$ with $r_n \to r$. Therefore, for some constant K_i indexing A^i, the bank's equilibrium strategy over $R^i \equiv supp\left\{r^f\left(A^i\right)\right\}$ satisfies

$$\left[1 - F^b(r)\right] r = K_i. \tag{32}$$

In addition, Eq. (32) holds over the entire common support $\left[\underline{r}, R^b\right]$. According to Lemma 4, for any bank quote $r \quad \left[\underline{r}, R^b\right]$, we can find an event $\hat{A} \quad P$ such that $F^b(r)$ is determined by the fintech's indifference condition over $\hat{A}$ and thus satisfies Eq. (32) with some $\hat{K}$ for $\hat{A}$. Then the continuity of $F^b(r)$ over $\left[\underline{r}, R^b\right]$ as shown in Lemma 5 leads to $K_i = K$ for any A^i, so the equilibrium bank strategy satisfies

$$\left[1 - F^b(r)\right] r = K, \text{ where } r \quad \left[\underline{r}, R^b\right]. \tag{33}$$

Second, conditional on making an offer, the fintech is indifferent across any rate in common support $\left[\underline{r}, R^b\right]$, regardless of event $A^i \quad P$. If a borrower defaults and repays $R^f(a) \equiv \frac{\beta a}{1-w} - 1$, as long as $R^f(a) \quad \left[\underline{r}, R^b\right]$, Eq. (33) still applies, so that $\left[1 - F^b\left(R^f(a)\right)\right] R^f(a) = K$; for lower types with $R^f(a) < \underline{r}$ or equivalently $a < \underline{a}^f(\underline{r})$, we have $1 - F^b\left(R^f(a)\right) = 0$. Hence, for any event $A^i \quad P$ with $m^f(A^i) > 0$, the fintech profit when quoting any $r \quad \left[\underline{r}, R^b\right]$ is

$$
\begin{aligned}
\pi^f\left(r, A^i\right) \quad & \int_{\underline{a}}^{\underline{a}^f(r)} \mathbf{1}_{A^i}\left[1 - F^b\left(R^f(a)\right)\right] \cdot R^f(a)\, dG(a) + \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \cdot \underbrace{\left[1 - F^b(r)\right] r}_{=K} \\
&= \int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{A^i} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{=1} \cdot R^f(a)\, dG(a) + \int_{\underline{a}^f(\underline{r})}^{\underline{a}^f(r)} \mathbf{1}_{A^i} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right] \cdot R^f(a)}_{=K} dG(a) \\
&\quad + K \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a) \\
&= \int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{A^i} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{A^i} dG(a),
\end{aligned}
$$

which is independent of the quote r.

Third, the equilibrium information structure is a single-threshold partition. The previous argument shows that the fintech only considers whether to make an offer. Note that there is no benefit in differentiating between the events upon which to reject the borrower (A with $m^f(A) = 0$) versus to randomly make an offer (A with $m^f(A) = 0$, indifferent whether to reject), because both lead to zero profits while the differentiation incurs information cost. Hence, equilibrium P and A^{offer}, and the fintech makes an offer with randomized interest rate iff A^{offer} occurs.

Further, each event is convex, resulting in a single-threshold partition. Suppose not, and thus there exist two subsets $\mathbf{a}^{\mathbf{rej}}, \mathbf{a}^{\mathbf{offer}}$ of equal measure such that

$$
\sup \mathbf{a}^{\mathbf{offer}} < \inf \mathbf{a}^{\mathbf{rej}} \quad \text{where} \quad \mathbf{a}^{\mathbf{rej}} \quad A^{rej}, \quad \mathbf{a}^{\mathbf{offer}} \quad A^{offer}, \quad \text{and} \quad \mathsf{P}\left(\mathbf{a}^{\mathbf{rej}}\right) = \mathsf{P}\left(\mathbf{a}^{\mathbf{offer}}\right).
$$

Then the fintech has a profitable deviation to the following partition

$$
\hat{P} \equiv \left\{\hat{A}^{rej} \equiv A^{rej} \quad \mathbf{a}^{\mathbf{offer}} \setminus \mathbf{a}^{\mathbf{rej}}, \hat{A}^{offer} \equiv A^{offer} \quad \mathbf{a}^{\mathbf{rej}} \setminus \mathbf{a}^{\mathbf{offer}}\right\}.
$$

To see this, when making lending decisions according to $\hat{P}$, the lending profits are higher

$$
\begin{aligned}
& \underbrace{\int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{a^{rej}} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{a^{rej}} dG(a)}_{\mathbf{a}^{\mathbf{rej}} \quad \hat{A}^{offer},\ \text{offer } r \quad \left[\underline{r}, R^b\right)} + \underbrace{\int_{\mathbf{a}^{\mathbf{offer}}} 0 \cdot g(a)\, da}_{\mathbf{a}^{\mathbf{offer}} \quad \hat{A}^{rej}, \text{reject}} \\
> & \underbrace{\int_{a^{rej}} 0 \cdot g(a)\, da}_{a^{rej} \quad A^{rej}, \text{reject}} + \underbrace{\int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{\mathbf{a}_2^{\mathbf{offer}}} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{\mathbf{a}_2^{\mathbf{offer}}} dG(a),}_{\mathbf{a}^{\mathbf{offer}} \quad A^{offer},\ \text{offer } r \quad \left[\underline{r}, R^b\right)}
\end{aligned}
$$

because $\sup \mathbf{a_2} < \inf \mathbf{a_1}$. Using Lemma 1, we show that the information cost stays the same due to and $\mathsf{P}\left(\mathbf{a^{rej}}\right) = \mathsf{P}\left(\mathbf{a^{offer}}\right)$. The profitable deviation leads to contradiction. Therefore,

$$P = P(\hat{a}) \equiv \{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\}, \tag{34}$$

where $\hat{a}$ serves as the screening threshold.

Last, I characterize the mixed strategy equilibrium. The fintech chooses $\hat{a}$ to maximize its net profits, facing bank competition that satisfies Eq. (33). Its boundary condition at $r = \underline{r}$ gives

$$K = \underline{r}.$$

Hence, the choice of $\hat{a}$ solves

$$\max_{\hat{a}} \mathsf{E}\left[\pi^f\left(r\left(A^i\right)\middle| A^i\right)\right] - cI\left(P(\hat{a})\right) dw,$$

where lending profits are given by

$$\mathsf{P}\left(A^i\right)\pi^f\left(r\left(A^i\right)\middle| A^i\right) = \begin{cases} 0, & A^i = [\underline{a}, \hat{a}), \\ (1-w)\, dH(w)\left[\int_{\hat{a}}^{\overline{a}} \min\left\{\underline{r}, R^f(a)\right\} dG(a)\right], & A^i = [\hat{a}, \overline{a}]. \end{cases}$$

and the entropy of a single-threshold partition is

$$I\left(P(\hat{a})\right) = -\left[G(\hat{a}) \log G(\hat{a}) + (1 - G(\hat{a})) \log (1 - G(\hat{a}))\right].$$

We take the first-order condition (FOC) with respect to $\hat{a}$:

$$(1-w)\, h(w)\, g(\hat{a})\left\{\mathbf{1}_{\hat{a} \geq \underline{a}^f(\underline{r})} \cdot (-\underline{r}) + \mathbf{1}_{\hat{a} < \underline{a}^f(\underline{r})} \cdot \left[-R^f(\hat{a})\right]\right\} + cg(\hat{a}) \log \frac{G(\hat{a})}{1 - G(\hat{a})} = 0,$$

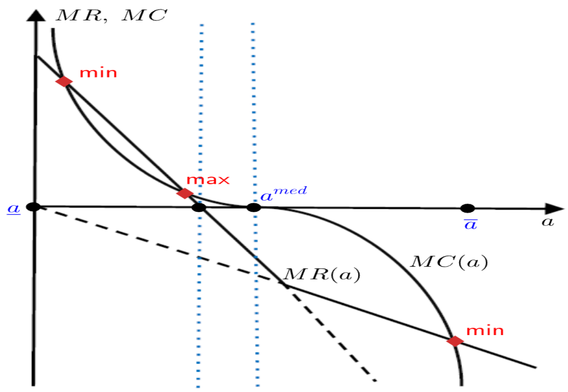
where $\underline{a}^f(r) \equiv \frac{(1-w)(1+r)}{\beta}$ is the lowest type who does not default on quote r. If $\hat{a} \geq \underline{a}^f(\underline{r})$, the marginal type $\hat{a}$ does not default on the lower-bound interest rate $\underline{r}$. In this case, we solve for $\underline{r}$ from the bank's indifference condition between $\underline{r}$ and R^b:

$$\underline{r} = G(\hat{a})\, R^b, \quad \text{if} \quad \hat{a} \geq \underline{a}^f(\underline{r}),$$

where the LHS corresponds to quoting $r^b = \underline{r}$ and getting all customers, and the RHS is about quoting $r^b = R^b$ and getting only those rejected by the fintech. The FOC is equivalent to

$$\underbrace{-(1-w)\, h(w) \min\left\{G(\hat{a})\, R^b, R^f(\hat{a})\right\}}_{MR} = \underbrace{-c \log \frac{G(\hat{a})}{1 - G(\hat{a})}}_{MC}. \tag{35}$$

For the local sufficiency condition, I argue that under Assumption 1 there exists at most one local maximum point $\hat{a}$ with $\hat{a} < \underline{a}^f(0) < a^{med}$, where $\underline{a}^f(0) \equiv \frac{1-w}{\beta}$ is the zero-NPV type to



fintech and a^{med} is the medium type. Denote by

$$Q(a) \triangleq -(1-w)\,h(w)\min\left\{G(a)\,R^b, R^f(a)\right\} + c\log\frac{G(a)}{1-G(a)};$$

then the FOC and SOC could be expressed as $Q(\hat{a}) = 0$ and $Q'(\hat{a}) < 0$ respectively. Under Assumption 1, we have $R^f\left(a^{med}\right) > 0$. I separate three regions $\left[\underline{a}, \underline{a}^f(0)\right)$, $\left[\underline{a}^f(0), a^{med}\right)$, $\left[a^{med}, \overline{a}\right]$, and the following figure illustrates the discussion with decomposed $Q(a) \equiv MR(a) - MC(a)$.

1. In the first region $\left[\underline{a}, \underline{a}^f(0)\right)$, we have $R^f(a) < 0 \le G(\hat{a})\,R^b$. Hence,

$$Q(a) = -(1-w)\,h(w)\,R^f(a) + c\log\frac{G(a)}{1-G(a)},$$
$$Q'(a) = -h(w)\,\beta + \frac{cg(a)}{G(a)\,(1-G(a))}.$$

   Under Assumption 3, $Q''(a) = \frac{d^2\left(c\log\frac{G(a)}{1-G(a)}\right)}{da^2} < 0$ and so $Q(a)$ is single-peaked, starting from strictly increasing at $\underline{a}$ ($Q'(\underline{a}) = \infty$). In addition, $Q(a)$ is negative at both endpoints,

$$Q(\underline{a}) = -\infty, \quad Q\left(\underline{a}^f(0)\right) = c\log\frac{G\left(\underline{a}^f(0)\right)}{1-G\left(\underline{a}^f(0)\right)} < c\log\frac{G\left(a^{med}\right)}{1-G\left(a^{med}\right)} = 0.$$

   Taken together, in this region, either $Q(a) < 0$, or there are two solutions $\hat{a} = \hat{a}_1, \hat{a}_2$ to $Q(\hat{a}) = 0$ with $Q(a) > 0$ when $\hat{a}_1 < a < \hat{a}_2$. The second scenario arises only when the unit information cost c is sufficiently small. In this scenario, $\hat{a}_1$ is a local minimum point with $Q'(\hat{a}_1) > 0$ and $\hat{a}_2$ is a local maximum point with $Q'(\hat{a}_2) < 0$.

2. In the second region $\left[\underline{a}^f(0), a^{med}\right)$, we have $R^f(a) \ge 0$ and $\log\frac{G(a)}{1-G(a)} < 0$, so

$$Q(a) = -(1-w)\,h(w)\min\left\{\underbrace{G(a)\,R^b}_{+}, \underbrace{R^f(a)}_{+}\right\} + \underbrace{c\log\frac{G(a)}{1-G(a)}}_{-} < 0.$$

3. In the third region $\left[a^{med}, \overline{a}\right]$, I show that any solution to $Q(\hat{a}) = 0$ must be a local minimum with $Q'(\hat{a}) > 0$. Denote by

$$Q_1(a) \triangleq -(1-w)\, h(w)\, R^f(a) + c \log \frac{G(a)}{1-G(a)},$$
$$Q_2(a) \triangleq -(1-w)\, h(w)\, G(a)\, R^b + c \log \frac{G(a)}{1-G(a)},$$

and then the solutions to $Q(\hat{a}) = 0$ must be a subset of solutions to $Q_1(\hat{a}) = 0$ or $Q_2(\hat{a}) = 0$. Notice that each Q_i for $i = \{1, 2\}$ has opposite signs at endpoints a^{med}, $\overline{a}$ with

$$Q_i\left(a^{med}\right) < 0, \quad Q_i(\overline{a}) = \infty.$$

By continuity, both $Q_i(\hat{a}) = 0$ have solutions, with the smallest one $\hat{a}_i \equiv \inf\left\{a \geq a^{med} \,|Q_i(a) = 0\right\}$ satisfying $Q_i'(\hat{a}_i) > 0$ due to $Q_i\left(a^{med}\right) < 0$. Moreover, I argue that for any $a \geq \hat{a}_i$ we have $Q_i'(a) > 0$, so there is no local maximum point in $[\hat{a}_i, \overline{a}]$, either. To see this, for $Q_1(a)$, we have $Q_1''(a) = \frac{d^2\left(c \log \frac{G(a)}{1-G(a)}\right)}{da^2} > 0$ (inequality comes from Assumption 3), so $Q_1'(a) \geq Q_1'(\hat{a}_1) > 0$ for $a \geq \hat{a}_1$. As for $Q_2'(a)$, we have

$$Q_2'(a) = g(a)\left\{-(1-w)\, h(w)\, R^b + \frac{c}{G(a)(1-G(a))}\right\},$$

where the term inside the curly brackets strictly increases in a. For any $a \geq \hat{a}_2$, we have $\frac{Q_2'(a)}{g(a)} \geq \frac{Q_1'(\hat{a}_2)}{g(\hat{a}_2)} > 0$ so that $Q_2'(a) > 0$.

In sum, there is at most one local maximum point $\hat{a}^* < \underline{a}^f(0)$ that arises under small information cost. As the endpoints ($\hat{a} = \underline{a}, \overline{a}$) correspond to not acquiring information, when c is sufficiently small, the local maximum $\hat{a}^*$ exists and is globally optimum. Therefore, the equilibrium is unique.

To complete the equilibrium characterization, I derive the fintech's CDF $F^f(r)$ upon $a \geq \hat{a}$ through the bank's indifference condition. The bank's lending profits when quoting $r \in \left[\underline{r}, R^b\right]$ is

$$\pi^b(r) = (1-w)\, dH(w) \cdot \left\{ \underbrace{G(\hat{a})}_{\text{fintech rejected}} + \underbrace{\left[1 - \max\left\{G(\hat{a}), G\left(\underline{a}^f(r)\right)\right\}\right]}_{\text{borrowers who compare quotes}} \underbrace{\left[1 - F^f(r)\right]}_{r^b < r^f} \right\} r, \tag{36}$$

which equals a constant $\pi^b\left(R^b\right) = (1-w)\, dH(w)\, G(\hat{a})\, R^b$. Hence, the fintech's strategy is

$$F^f(r) = 1 - \frac{G(\hat{a})}{1 - \max\left\{G(\hat{a}), G\left(\underline{a}^f(r)\right)\right\}} \frac{R^b - r}{r}, \tag{37}$$

and its boundary condition $F^f(\underline{r}) = 0$ gives

$$\underline{r} = \frac{G(\hat{a})\, R^b}{G(\hat{a}) + 1 - G\left(\underline{a}^f(r)\right)},$$

where we used the result that $\hat{a} < \underline{a}^f(0) < \underline{a}^f(\underline{r})$. ☐

6.2 Proof of Proposition 1

Lemma 6. *When $w \geq 1-\theta$, equilibrium screening threshold $\hat{a} < a^{med}$ (medium type), or $G(\hat{a}) < \frac{1}{2}$, and $R^f(\hat{a}) < 0$.*

Proof. See the local sufficiency discussion of $\hat{a}$ in Section 6.1.3. ☐

Proof of Proposition 1

Proof. I first construct the net profits $\tilde{Y}(\hat{a}, w)$ *assuming information acquisition* (interior $\hat{a}$)

$$\tilde{Y}(\hat{a}, w)\ ,\ \max_{\hat{a}\ (\underline{a},\overline{a})}\left[\pi^f(\hat{a}; w) - cI(\hat{a})\,dw\right]$$
$$\begin{cases} (1-w)\,h(w)\cdot\int_{\hat{a}}^{\overline{a}} R^f(a)\,dG(a) - cI(\hat{a}), & w < 1-\theta, \\ (1-w)\,h(w)\cdot\left\{\int_{\hat{a}}^{\underline{a}^f(\underline{r})} R^f(a)\,dG(a) + \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right]\underline{r}\right\} - cI(\hat{a}), & w \geq 1-\theta. \end{cases}$$

The gain from information is the gap between $\tilde{Y}(\hat{a})$ and an uninformed fintech's profits,

$$\Delta\tilde{Y}(\hat{a}, w)\quad \begin{cases} -(1-w)\,h(w)\cdot\int^{\hat{a}} R^f(a)\,dG(a) - cI(\hat{a}), & w < 1-\theta, \\ (1-w)\,h(w)\cdot\left\{\int_{\hat{a}}^{\underline{a}^f(\underline{r})} R^f(a)\,dG(a) + \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right]\underline{r}\right\} - cI(\hat{a}), & w \geq 1-\theta, \end{cases}$$

where uninformed fintech makes zero profits when the bank is present $w \geq 1-\theta$.

Using the envelope theorem, when $w < 1-\theta$, the fintech has less incentive to acquire information when borrowers become wealthier,

$$\frac{\partial\Delta\tilde{Y}(\hat{a}, w)}{\partial w} = -\int^{\hat{a}} \underbrace{\frac{\partial\left[(1-w)\,h(w)\,R^f(a)\right]}{\partial w}}_{>0} dG(a) < 0.$$

When $w = 1-\theta$, we have $R^b = 0$, so $\underline{r} \leq R^b = 0$ and $\Delta\tilde{Y}(\hat{a}, w) < 0$ and the fintech does not acquire information. By continuity, this applies to a region of mid-ranged markets $[1-\theta, \hat{w})$. When w is sufficiently high, the fintech acquires information; otherwise a profitable deviation is identifying borrowers with $a \geq \hat{a} = \overline{a} -$ (at negligible information cost) and undercut the bank at $r^f = \underline{r}$. By continuity, this applies to a region of wealthy borrowers.

More formally, applying the envelope theorem when $w \geq 1-\theta$,

$$\frac{\partial\Delta\tilde{Y}(\hat{a})}{\partial w} = \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right]\frac{\partial\left[(1-w)\,h(w)\,\underline{r}(w)\right]}{\partial w}\qquad\frac{\partial\underline{r}(w)}{\partial w},$$

where $\underline{r}$ satisfy the bank's indifference condition (regardless of whether the fintech acquires information in equilibrium),

$$M\ ,\ \underline{r}\left[G(\hat{a}(w)) + 1 - G\left(\underline{a}^f(\underline{r}, w)\right)\right] - R^b(w)\,G(\hat{a}(w)) = 0. \tag{38}$$

We know that

$$\frac{\partial \underline{a}^f\left(\underline{r},w\right)}{\partial w}<0,\ \frac{\partial R^b\left(w\right)}{\partial w}>0,$$

and from FOC and the implicit function theorem,

$$\frac{\partial \hat{a}}{\partial w}=-\frac{\frac{\partial Q}{\partial w}}{\frac{\partial Q}{\partial \hat{a}}}=\frac{\frac{\partial\left[(1-w)h(w)R^f(a)\right]}{\partial w}}{\frac{\partial Q}{\partial \hat{a}}}<0,$$

where $Q\left(\hat{a}\right)\ ,\ -\left(1-w\right)h\left(w\right)R^f\left(a\right)-c\log\frac{G(\hat{a})}{1-G(\hat{a})}=0$ corresponds to the FOC and $\frac{\partial Q(\hat{a})}{\partial \hat{a}}<0$ corresponds to the SOC. Then applying the implicit function theorem to Eq. (38), we have

$$\frac{\partial \underline{r}}{\partial w}=-\frac{\frac{\partial M}{\partial w}}{\frac{\partial M}{\partial \underline{r}}}=-\frac{-\left(R^b-\underline{r}\right)g\left(\hat{a}\right)\underbrace{\frac{\partial \hat{a}}{\partial w}}_{<0}-\underline{r}g\left(\underline{a}^f\left(\underline{r}\right)\right)\underbrace{\frac{\partial \underline{a}^f\left(\underline{r},w\right)}{\partial w}}_{<0}-\underbrace{\frac{\partial R^b}{\partial w}}_{>0}G\left(\hat{a}\left(w\right)\right)}{G\left(\hat{a}\right)+1-G\left(\underline{a}^f\left(\underline{r}\right)\right)-\underline{r}g\left(\underline{a}^f\left(\underline{r}\right)\right)\frac{\partial \underline{a}^f}{\partial \underline{r}}}.$$

When $w\rightarrow\left(1-\theta\right)^+$, we have $\underline{r}\rightarrow 0, R^b\rightarrow 0$, and $\frac{\partial\Delta\tilde{Y}(\hat{a})}{\partial w}\quad\frac{\partial \underline{r}}{\partial w}>0$; when w is sufficiently high such that $G\left(\hat{a}\right)\rightarrow 0^+$, we have $\frac{\partial\Delta\tilde{Y}(\hat{a})}{\partial w}\quad\frac{\partial \underline{r}}{\partial w}<0$.

Therefore, the fintech does not acquire information in mid-ranged markets, and competition becomes fiercer in wealthy markets ($\frac{\partial \underline{r}}{\partial w}<0$). □

6.3 Proof of Proposition 2

Proof. I study the comparatives of $\hat{a},\underline{r},F^j\left(r\right)$ in response to β and c. We have the FOC

$$Q\left(\hat{a},\beta,c\right)\ ,\ -\left(1-w\right)h\left(w\right)R^f\left(\hat{a}\right)+c\log\frac{G\left(\hat{a}\right)}{1-G\left(\hat{a}\right)}=0.$$

From the Implicit Function Theorem, we have

$$\frac{\partial \hat{a}}{\partial \beta}=-\frac{\frac{\partial Q}{\partial \beta}}{\frac{\partial Q}{\partial \hat{a}}}=\frac{\hat{a}}{\underbrace{\frac{\partial Q}{\partial \hat{a}}}_{SOC<0}}<0,$$

which says an improvement in enforcement lowers the screening threshold as it reduces the cost of serving lemons; and

$$\frac{\partial \hat{a}}{\partial c}=-\frac{\frac{\partial Q}{\partial c}}{\frac{\partial Q}{\partial \hat{a}}}=-\frac{\overbrace{\log\frac{G\left(\hat{a}\right)}{1-G\left(\hat{a}\right)}}^{<0\text{ as }\hat{a}<a^{med}}}{\underbrace{\frac{\partial Q}{\partial \hat{a}}}_{SOC<0}}<0,$$

which says an improvement in information technology tightens the screening threshold and squeezes out more lemons.

Using Lemma 6, we have $R^f(\hat{a}) < \underline{r}$, where the equilibrium $\underline{r}$ is determined by the bank's indifference condition $\pi^b(\underline{r}) = \pi^b\left(R^b\right)$, or $M(\underline{r}, \beta, c)\ ,\ \underline{r}\left[G(\hat{a}) + 1 - G\left(\underline{a}^f(\underline{r}, \beta)\right)\right] - R^b G(\hat{a}) = 0$. From the implicit function theorem, we have

$$\frac{\partial \underline{r}}{\partial \beta} = -\frac{\frac{\partial M}{\partial \beta}}{\frac{\partial M}{\partial \underline{r}}} = -\frac{-\left(R^b - \underline{r}\right) g(\hat{a}) \underbrace{\frac{\partial \hat{a}}{\partial \beta}}_{<0} - \underline{r} g\left(\underline{a}^f(\underline{r}, \beta)\right) \underbrace{\frac{\partial \underline{a}^f}{\partial \beta}}_{<0}}{G(\hat{a}) + 1 - G\left(\underline{a}^f(\underline{r}, \beta)\right) - \underline{r} g\left(\underline{a}^f(\underline{r}, \beta)\right) \underbrace{\frac{\partial \underline{a}^f}{\partial \underline{r}}}_{>0}},$$

$$\frac{\partial \underline{r}}{\partial c} = -\frac{\frac{\partial M}{\partial c}}{\frac{\partial M}{\partial \underline{r}}} = -\frac{-\left(R^b - \underline{r}\right) g(\hat{a}) \underbrace{\frac{\partial \hat{a}}{\partial c}}_{<0}}{G(\hat{a}) + 1 - G\left(\underline{a}^f(\underline{r}, \beta)\right) - \underline{r} g\left(\underline{a}^f(\underline{r}, \beta)\right) \underbrace{\frac{\partial \underline{a}^f}{\partial \underline{r}}}_{>0}}.$$

In other words, $\frac{\partial \underline{r}}{\partial \beta}$ and $\frac{\partial \underline{r}}{\partial c}$ have the opposite sign of the denominator $\frac{\partial M}{\partial \underline{r}} = \frac{\partial \pi^b(\underline{r})}{\partial \underline{r}}$. As β or c increase, the fintech competes for more borrowers, and the fiercer competition leads the equilibrium $\underline{r}$ to go the opposite of the bank's preferred direction.

The change in the lender's mixed strategy CDFs F^b, F^f could be derived from the change in the boundary conditions. From $F^b(r) = 1 - \frac{\underline{r}}{r}$, a higher (lower) equilibrium $\underline{r}$ make the bank's strategy less aggressive in the sense of first order stochastic dominance; i.e., for $\underline{r} > \underline{r}$, $F^b(r; \underline{r}) \ ^{FOSD}$ $F^b(r; \underline{r})$. From $F^f(r) = 1 - \frac{R^b - r}{1 - G\left(\underline{a}^f(r)\right)} \cdot G(\hat{a})$, we know that the fintech bids more aggressively in the sense of FOSD when β and c increase ($\hat{a}$ decreases).

Last, I examine how the lenders' profits change. The bank's equilibrium lending profit is

$$\pi^b = (1 - w)\, dH(w) \cdot G(\hat{a}) R^b \quad G(\hat{a}).$$

Hence, we have

$$\frac{\partial \pi^b}{\partial \beta} \leq 0, \ \frac{\partial \pi^b}{\partial c} < 0.$$

The effects on the fintech's profits are less clear: it benefits from better lending technology but may thus face fiercer competition. To see this, let $Y^f(\hat{a})$ denote the fintech's net profits (net of information cost),

$$\begin{aligned} Y^f(\hat{a}) &\equiv \pi^f - cI(P(\hat{a})) \\ &= (1 - w)\, dH(w) \cdot \int_{\hat{a}}^{\overline{a}} \min\left\{R^f(a), \underline{r}\right\} dG(a) - cI(P(\hat{a})) \\ &= (1 - w)\, dH(w) \cdot \left\{\int_{\hat{a}}^{\underline{a}^f(\underline{r})} R^f(a)\, dG(a) + \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right] \underline{r}\right\} - cI(P(\hat{a})). \end{aligned}$$

By the envelope theorem, we have

$$\frac{\partial Y^f}{\partial \beta} \quad \left[\int_{\hat{a}}^{\underline{a}^f(\underline{r})} \frac{a}{1-w} dG(a) + \left(1 - G\left(\underline{a}^f(\underline{r})\right)\right) \frac{\partial \underline{r}}{\partial \beta}\right],$$

$$\frac{\partial Y^f}{\partial c} = (1-w)\, dH(w) \cdot \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right] \frac{\partial \underline{r}}{\partial c} - I(P(\hat{a})).$$

Hence, whether the fintech benefits from improvement in technology depends on the resulting competition. For example, from the proof of Proposition 1 we know that $\frac{\partial M}{\partial \underline{r}} > 0$ for sufficiently high w, so $\underline{r}$ decreases as β or c increases. In this case, we have $\frac{\partial Y^f}{\partial c} < 0$, i.e., the fintech benefits from an improvement in information acquisition.

$\square$

7 Online Appendix

7.1 Appendix: Textual Analysis of Fintechs

This section explains the textual analysis used to create Figure 1, which is based on company descriptions from Pitchbook.

To identify fintech lenders, I begins with selecting companies whose vertical variable include "fintech" by as assigned by Pitchbook. Although Pitchbook provides further classification in "keywords" variables such as payment, crypto, banking-as-a-service, and others, the classification is relatively arbitrary. Instead, I identify a company as fintech lender if its company description includes keywords such as "lending platform," "financing solutions," "overdraft," and others. This results in a sample of 867 fintech lenders for Figure 1.

Next, more specific keywords are employed to categorize fintech lenders based on lending services (Panel A) and technology (Panel B). Although classifications are not exclusive, overlaps between categories are rare. The count of lenders in the figure might be underestimated due to the brevity of company descriptions.

For instance, for service classification, lenders providing working capital loans are identified using keywords like "sales," "receivables," "invoices," "working capital;" Personal loan providers are identified using keywords like "buy now pay later." For technology classification, Fintech lenders offering digitalized services are identified using keywords like "online," "web-based," while those using algorithmic models are identified using keywords like "machine learning," "algorithmic," "artificial intelligent." Due to the theoretical nature of the paper, the full list of keywords used for the textual analysis is not provided in the Appendix.

7.2 Bank Enforcement on Cash Flows

In this part, we show that the main result of the fintech's single-threshold information acquisition does not rely on the private value setting. Specifically, we enable the bank to enforce on a fraction $\gamma > 0$ in addition to the physical collateral, i.e.,

$$\Phi^b(a) = \theta + \gamma a,$$

so that the bank also cares about the underlying productivity of the borrower. We show that credit market equilibrium is similar to that characterized in Theorem 1 with adjustment on lenders' interest rate distributions.

Now that whether a borrower defaults on a bank's loan depends on a as well as w, it is convenient to introduce $\underline{a}^b(r; w)$ and $R^b(a; w)$ respectively as the marginal productivity type who fully repays bank's quote r and the maximum rate that the bank is able to enforce on type a,

$$\underline{a}^b(r; w) \equiv \frac{(1+r)(1-w) - \theta}{\gamma}, \tag{39}$$

$$R^b(a; w) \equiv \frac{\theta + \gamma a}{1-w} - 1. \tag{40}$$

Recall that we have defined the counterparts for the fintech lender, $\underline{a}^f(r; w)$ and $R^f(a; w)$ in the main text.

Lemma 7. *Suppose that a borrower receives two o ers r^b, r^f. Define*

$$\check{a} \equiv \begin{cases} \frac{\theta}{\beta-\gamma}, & \text{if } \beta > \gamma, \\ \infty, & \text{if } \beta \leq \gamma. \end{cases}$$

i) For borrowers with $a \leq \check{a}$, she chooses the bank's o er i both $r^b \leq r^f$ and $a \geq \underline{a}^f\left(r^b; w\right)$;

ii) For borrowers with $a > \check{a}$, she chooses the fintech's o er i both $r^f \leq r^b$ and $a \geq \underline{a}^b\left(r^f; w\right)$.

Proof. Note that $R^b(a) > R^f(a)$ when $a < \check{a}$ and $R^b(a) < R^f(a)$ when $a > \check{a}$.

i) Case $a \leq \check{a}$: in this case $R^b(a) \geq R^f(a)$ and we show that borrower choice is similar as that in the baseline private value setting, i.e., the fintech is subject to adverse selection when competing against the bank.

If $r^b \leq r^f$, there are two subcases depending on whether $R^f(a) \leq r^b$. For borrowers with $R^f(a) \leq r^b$, they default on the fintech's offer as $r^f \geq r^b \geq R^f(a)$ so the actual borrowing cost with the fintech is $R^f(a)$; since $R^f(a) \leq R^b(a)$ (from $a \leq \check{a}$) and $R^f(a) \leq r^b$, we have $R^f(a) = \min\left\{r^f, R^f(a)\right\} \leq \min\left\{r^b, R^b(a)\right\}$ and these borrowers would choose the fintech. For borrowers with $r^b < R^f(a)$, they make full payments to the bank's offer as $r^b \leq R^f(a) < R^b(a)$, so the actual borrowing cost with the bank is r^b; since $r^b \leq R^f(a)$ and $r^b \leq r^f$, we have $\min\left\{r^b, R^b(a)\right\} = r^b \leq \min\left\{r^f, R^f(a)\right\}$ and borrowers would choose the bank.

If instead $r^b > r^f$, since $R^b(a) \geq R^f(a)$ as well, we have $\min\left\{r^b, R^b(a)\right\} \geq \min\left\{r^f, R^f(a)\right\}$ and borrowers choose the fintech.

ii) Case $a > \check{a}$: in this case $R^b(a) < R^f(a)$, and we show that borrower choice is reversed.

If $r^b \leq r^f$, since $R^b(a) < R^f(a)$ as well, we have $\min\left\{r^b, R^b(a)\right\} \leq \min\left\{r^f, R^f(a)\right\}$ and borrowers choose the bank.

If $r^b > r^f$, there are two subcases depending on whether $R^b(a) \leq r^f$. For borrowers with $R^b(a) \leq r^f$, they will default on the bank's offer as $r^b > r^f \geq R^b(a)$ so the actual borrowing cost with the bank is $R^b(a)$; since $R^b(a) < R^f(a)$ (from $a > \check{a}$) and $R^b(a) \leq r^f$, we have $\min\left\{r^b, R^b(a)\right\} = R^b(a) \leq \min\left\{r^b, R^f(a)\right\}$ and these borrowers would choose the bank. For borrowers with $R^b(a) > r^f$, they make full payments to the fintech's offer as $r^f < R^b(a) < R^f(a)$, so $\min\left\{r^f, R^f(a)\right\} = r^f$; since $r^f < r^b$ and $r^f < R^b(a)$, we have $\min\left\{r^f, R^f(a)\right\} = r^f < \min\left\{r^b, R^b(a)\right\}$ and borrowers choose the fintech. □

Proposition 5. *Suppose $w \geq 1-\theta$ so that the bank is present.the fintech rejects borrowers with $a < \hat{a}$ and makes an o er upon $a \geq \hat{a}$.*

1. The fintech's optimal information acquisition policy separates two intervals with an endogenous cutoff $\hat{a}$ and rejects borrowers with $a < \hat{a}$:

$$P^{f,w} = \left\{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\right\}; \tag{41}$$

2. The bank always lends while the fintech lends when $a \geq \hat{a}$. The offered interest rates $\left\{r^b, r^f\right\}$

are randomized over a common support $\left[\underline{r}, R^b(\hat{a}) \equiv \frac{\theta+\gamma\hat{a}}{1-w} - 1\right]$ according to

$$F^b(r) = \begin{cases} 1 - \frac{\underline{r}}{r}, & r \in \left[\underline{r}, R^b(\hat{a})\right), \\ 1, & r = R^b(\hat{a}), \end{cases} \tag{42}$$

$$F^f(r|a \geq \hat{a}) = 1 - \frac{\frac{1}{r}\int_{\underline{a}^b(r)}^{\hat{a}} R^b(a)\,dG(a) - \left[G(\hat{a}) - \max\left\{0, G\left(\underline{a}^b(r)\right)\right\}\right]}{1 - G(\max\{\underline{a}^f(\underline{r}), \hat{a}\})} \tag{43}$$

where $\underline{r}$ satisfies $F^f(\underline{r}|a \geq \hat{a}) = 0$.

3. The endogenous screening threshold $\hat{a}$ adopted by the fintech satisfies

$$\underbrace{(1-w)\,h(w)\min\left\{R^f(\hat{a}), \underline{r}\right\}}_{MR:\text{ profit from marginal type}} = \underbrace{c\log\left[\frac{1-G(\hat{a})}{G(\hat{a})}\right]}_{MC:\text{ marginal information cost}}$$

Proof. We briefly argue that the fintech lender does not deviate from the stated strategy. In addition to its lending technology, the competition environment that it faces also remains the same. To see this, the stated equilibrium bank strategy has the same structure as in Theorem 1. Moreover, borrower's choice rule remains unchanged given the bank strategy: as $r^b \leq R^b(\hat{a})$, bank loans are endogenously riskless in competition for borrowers with $a \geq \hat{a}$; according to Lemma 7, borrower choice remains the same.[21] Hence, we refer to the proof of Theorem 1 for the argument on the fintech lender. Note that the proof is robust to the new interest rate supports $\underline{r}, R^b(\hat{a})$ and the cutoff $\hat{a}$.

Now we argue that the bank does not have incentive to deviate. First, the bank is indifferent across any $r^b \in \left[\underline{r}, R^b(\hat{a})\right]$. In this range, bank loans are risky only for borrowers with $a < \hat{a}$, and lending profits

$$\pi^b\left(r^b; w\right) = \underbrace{\int_{\underline{a}}^{\hat{a}}}_{\text{no fintech offer}} \min\left\{r^b, R^b(a)\right\} dG(a) + \left[1 - G\left(\max\left\{\hat{a}, \underline{a}^f(\underline{r})\right\}\right)\right] \underbrace{\left[1 - F^f\left(r^b\right)\right]}_{\text{bank quote is lower}} r^b.$$

Given the fintech's strategy Eq. (42) and defining $\tilde{a} \equiv \max\left\{\hat{a}, \underline{a}^f(\underline{r})\right\}$, the previous profits equal

$$\begin{aligned} &\int_{\underline{a}}^{\hat{a}} \min\left\{r^b, R^b(a)\right\} dG(a) - r^b\left[G(\hat{a}) - \max\left\{0, G\left(\underline{a}^b(r)\right)\right\}\right] + \int_{\underline{a}^b(r)}^{\hat{a}} R^b(a)\,dG(a) \\ = &\int_{\underline{a}}^{\hat{a}} R^b(a)\,dG(a), \end{aligned}$$

which is the maximum bank profits from its captured borrowers with $a < \hat{a}$.

Second, the bank earns no greater profit if it were to quote r^b outside of the equilibrium support.

[21] Specifically, we check when borrowers choose the fintech lender, given the stated equilibrium bank strategy. Borrowers with $\hat{a} \leq a \leq \check{a}$ choose the fintech when either $r^f \leq r^b$ and $r^b \geq R^f(a)$, which is the same as in the baseline. Borrowers with $a > \check{a}$ choose the fintech when $r^f \leq r^b$ and condition $r^b \geq R^f(a)$ always fail.

Suppose that the bank quotes $r^b > \overline{r}$. For borrowers with $a \geq \hat{a}$, since $R^b(a) \geq \overline{r} = R^b(\hat{a})$ as well and the fintech always quote below $\overline{r}$, these borrowers always choose the fintech's offer. As a result, the bank receives the same lending profits as in equilibrium, $\int_{\underline{a}}^{\hat{a}} R^b(a)\, dG(a)$, so it is wlog to assume that $r^b \leq \overline{r}$. To check the bank's deviation incentive to quote a lower rate $r^b < \underline{r}$, suppose that it quotes $r^b = \underline{r} -\ $. If $\hat{a} \geq \underline{a}^f(\underline{r})$, the bank's profits drops by $\int_{\max\{\underline{a},\underline{a}^b(\underline{r})\}}^{\overline{a}} dG > 0$. If $\hat{a} < \underline{a}^f(\underline{r})$, the bank gains additional customer of type $\underline{a}^f(\underline{r} -\ )$ but loses   on existing customers. The resulting change in its lending profits is $-\ \left\{\int_{\max\{\underline{a},\underline{a}^b(\underline{r})\}}^{\hat{a}} dG + \int_{\underline{a}^f(\underline{r})}^{\overline{a}} dG - \underline{r}\right\}$ which is negative under Assumption 2.

Therefore, we have shown that the constructed strategies correspond to an equilibrium. □

Remark 3. Proposition 5 shows that the credit competition outcome would be similar even if the bank also cares about the underlying productivity for fundamental reasons. The paper highlights the difference of the new fintech lending and thus focuses on the extreme case of the "private value setting", and this part shows that the main result does not rely on the private value assumption.

Remark 4. With the goal of showing robustness, we focus on markets $w \geq 1 - \theta$ and leave the full characterization of credit market equilibrium across w for follow-up research. One difference is that the bank with better enforcement technology would also enter some riskier markets with $w < 1 - \theta$. The results may still be robust, because the fintech may not enter these "mid-w" markets conditional on bank presence.

7.3 Perfect Information Benchmark

As the fintech perfectly observes productivity a, I focus on riskless fintech loans with

$$r^f(a) \leq R^f(a).$$

Technically, I need the following assumption so that riskless fintech loans are not restricting the fintech's strategies in equilibrium.

Assumption 4.

$$\frac{\sup g(a)\left(\beta a - (1 - \overline{w})\right)^2}{\beta G\left(\frac{1-\overline{w}}{\beta}\right)} \leq R^b(1 - \overline{w}).$$

Two points are worth noting. First, as the bank only cares the distribution of fintech quotes $F^f(r)$, it is w.l.o.g to focus on increasing $r^f(a)$. Second, as there is no deadweight loss when default occurs, multiplicity may arise due to payoff equivalent risky loans.

Proposition. *The equilibrium is unique:*

1. *When $w < 1 - \theta$, the monopolist fintech rejects borrowers with $a < \underline{a}^f(0)$, and otherwise o ers the highest rate $R^f(a)$;*

2. *When $w \geq 1 - \theta$, the bank makes an o er with randomized interest rate r^b $\left[\underline{r}^b, R^b\right]$ according to CDF*

$$F^b(r; w) = 1 - \frac{\underline{r}^b}{r}, \tag{44}$$

where $\underline{r}^b = R^b G\left(\underline{a}^f(0)\right)$ *and there is a mass point of size* $G\left(\underline{a}^f(0)\right)$ *at* R^b. *The fintech's strategy is summarized as*

$$\begin{cases} m^f(a) = 0, & \text{if } a < \underline{a}^f(0), \\ m^f(a) = 1,\ r^f(a) = R^f(a), & \text{if } \underline{a}^f(0) \le a < \underline{a}^f\left(\underline{r}^b\right), \\ m^f(a) = 1,\ r^f(a) < R^f(a), & \text{if } a \ge \underline{a}^f\left(\underline{r}^b\right), \end{cases}$$

where $\underline{a}^f(r)$ *is given in Eq. (9), and* $r^f(a)$ *is determined by*
In addition, bank profit is the monopolist profits on its captured borrowers,

$$\pi^b \quad R^b \cdot G\left(\underline{a}^f(0)\right);$$

The fintech's profit from each borrower type a *is*

$$\pi^f\left(r^f \middle| a; w\right) \quad \begin{cases} 0, & \text{if } a < \underline{a}^f(0), \\ R^f(a), & \text{if } \underline{a}^f(0) \le a < \underline{a}^f\left(\underline{r}^b\right), \\ \underline{r}^b, & \text{if } a \ge \underline{a}^f\left(\underline{r}^b\right). \end{cases}$$

Proof. **Step 1.1** The bank uses mixed strategy, and $\pi^b > 0$.

For borrowers with $\underline{a} \le a < \underline{a}^f(0)$, it is a dominant strategy for the fintech to reject them. Suppose in equilibrium the bank uses pure strategy and offers r^b. In this conjectured equilibrium, the fintech must charge $r^f = r^b -$ for all borrowers with $a \ge \underline{a}^f\left(r^b - \quad\right)$ which is the best response. Hence, with the resulting bank profit is $G\left(\underline{a}^f(0)\right) \cdot r^b$, the bank has incentive to deviate to $r^b = R^b$. Contradiction. As a result, the bank has captured borrowers with $\pi^b > 0$, and the interest rates must satisfy $r^b > 0$ on the support of bank's rate.

Step 1.2 Well-behaved mixed strategy $F^b(r)$ and $F^f(r)$ (the fintech's distribution faced by the bank)

It is useful to replicate lender profits here,

$$\pi^f\left(r^f\right) \quad \underbrace{\int^{\underline{a}(r^f)}}_{\text{low } a} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{\text{winning prob}} \cdot \underbrace{R^f(a)}_{\text{repayment}} dG(a) + \underbrace{\int_{\underline{a}(r^f)} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^b\left(r^f\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^f}_{\text{repayment}}, \tag{45}$$

$$\pi^b\left(r^b\right) \quad G\left(\underline{a}^f(0)\right) \cdot r^b + \underbrace{\int_{\underline{a}(r^b)} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^f\left(r^b\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^b}_{\text{repayment}}, \tag{46}$$

which highlights the effective cost with the fintech. The standard argument in literature (Varian, 1980, for example) is, if in a conjectured equilibrium a lender's distribution is unsmooth, its competitor's strategy must also be unsmooth locally, which usually results in profitable deviations. From Eq. (45) and (46), if competitor's distribution is unsmooth at r^j, the term

$$\left[1 - F^j\left(r^j\right)\right] r^j$$

would be driving lender j's incentive around r^j, so the argument would be robust.

Specifically, first, there is no interior mass point in $F^j(\cdot)$, and one lender could have a mass point at R^b. Otherwise suppose lender j has a mass point at $\hat{r} < R^b$ in equilibrium. Then in this conjectured equilibrium, $(\hat{r}, \hat{r} + \ )$ is not a subset of the other lender j 's support: Suppose not; then on any borrowers that lender j would charge $\hat{r} +$ potentially, it would strictly prefer charging $\hat{r} -$. It follows that one profitable deviation for lender j is to increase the quote at mass point to $r^j \quad (\hat{r}, \hat{r} + \ )$.[22] Contradiction. The only exception is when the point mass is at $\hat{r} = R^b$. If both lenders have a point mass, then both have a profitable deviation by undercutting the competitor.

Second, lenders' upper support $\bar{r}^b = \bar{r}^f \equiv \bar{r}$, and lower support $\underline{r}^f = 0 < \underline{r}^b$. It is wlog to focus on $\bar{r}^f \leq \bar{r}^b$. This is because when $r^f > \bar{r}^b$, the fintech's profit is a constant $\int^{\underline{a}(\bar{r}^b)} \left[1 - F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a)$ (the first term in Eq. 45) irrelevant of r^f. If $\bar{r}^f < \bar{r}^b$, in the conjectured equilibrium, the bank with captured borrowers must put all weight of $r^b \quad \left[\bar{r}^f, \bar{r}^b\right]$ at R^b. Then the fintech has a profitable deviation by marginally increasing the interest rate $\bar{r}^f -$ to $\bar{r}^f +$ (on the corresponding borrowers). As for lower supports, we have $\underline{r}^b > 0$ as bank profit is positive; within riskless loans, we have $\underline{r}^f = 0$ charged on the borrower with zero NPV.

Third, there is no (interior) gap. Let $(r\ , r\ )$ refer to the potential gap. Suppose the bank has a gap. Then for the borrowers that the fintech charges r , it is a profitable deviation to marginally increase the interest rate to $r +$ (as the demand does not change). Suppose the fintech has gap in $(r\ , r\ )$. According to Eq. (46), the bank's profit when charging $r^b \quad [r\ , r\ ]$ is $G\left(\underline{a}^f(0)\right) r^b + G\left(\underline{a}(r^b)\right)\left[1 - F^f(r\ )\right] r^b$. So the bank cannot be indifferent across $[r\ , r\ ]$ and has a profitable deviation. Contradiction.

Step 1.3 The lender strategies in Proposition 7.3 constitute an equilibrium.

Bank strategy is such that given $F^b(r)$ the fintech's strategy $r^f(a)$ maximizes its profits for each $a \geq \underline{a}^f\left(\underline{r}^b\right)$, i.e.,

$$r^f(a) = \arg\max\left(1 - F^b\left(r^f(a)\right)\right) r^f(a) \qquad (47)$$
$$s.t.\ r^f(a) \leq R^f(a).$$

If $r^f(a) < R^f(a)$ holds genericall, FOC for r^f is

$$-f^b\left(r^f\right) r^f + 1 - F^b\left(r^f\right) = 0,$$

which leads to

$$F^b(r) = \begin{cases} 1 - \frac{\underline{r}^b}{r}, & \underline{r}^b \leq r < R^b, \\ 1, & r = R^b. \end{cases} \qquad (48)$$

The sufficiency of FOC could be verified by the SOC

$$-2f^b(r) - \frac{df^b(r)}{dr} \cdot r = -\frac{2\underline{r}^b}{r^2} - \left(-\frac{2\underline{r}^b}{r^3}\right) \cdot r = 0.$$

If instead $r^f(a\ ) = R^f(a\ )$ for some neighborhood of a , we would have $-f^b\left(r^f(a\ )\right) r^f + 1 -$

[22]If lender j is the fintech, this deviation could still be focused on riskless loans.

$F^b\left(r^f(a)\right) > 0$ and $F^b(r) \leq 1 - \frac{\underline{r}^b}{r}$.[23] This case will be ruled out when deriving the fintech's strategy.

From $F^b(r) \leq 1 - \frac{\underline{r}^b}{r}$, it follows that $F^b(r)$ has a point mass at $\overline{r}$ while $F^f(r)$ is open at $\overline{r}$. In addition, as the bank has captured borrowers, $\overline{r} = R^b$, or otherwise the bank has a profitable deviation to increase $\overline{r}$.

Fintech's strategy over $r^f \quad \left[\underline{r}^b, R^b\right)$ is such that given $F^f(r)$, the bank is indifferent across $\left[\underline{r}^b, R^b\right]$. As the bank only cares about $F^f(r)$, it is w.l.o.g. to focus on increasing $r^f(a)$; and since $F^f(r)$ is smooth, $r^f(a)$ is *strictly* increasing. This allows me to introduce the inverse $\varphi(r) \equiv \left[r^f(a)\right]^{-1}$ to denote the marginal borrower who is charged with $r^f = r$. Then bank profit is

$$\pi^b(r) \quad \left[\underbrace{G\left(\underline{a}^f(0)\right)}_{\text{fintech rejected}} + \underbrace{1 - G(\varphi(r))}_{\text{winning prob}}\right] r.$$

The indifference condition pins down $r^f(a)$ over $\left[\underline{a}^f\left(\underline{r}^b\right), \overline{a}\right]$ by the following ODE

$$\frac{dr^f(a)}{da} = \frac{r(a)\, g(a)}{G\left(\underline{a}^f(0)\right) + 1 - G(a)}, \tag{49}$$

The boundary conditions are

$$r^f\left(\underline{a}^f\left(\underline{r}^b\right)\right) = R^f\left(\underline{a}^f\left(\underline{r}^b\right)\right) = \underline{r}^b, \;\; r^f(\overline{a}) = R^b,$$

where $\underline{r}^b$ is pinned down by the bank's indifference condition between $\underline{r}^b$ and R^b:

$$\left[G\left(\underline{a}^f(0)\right) + 1 - G\left(\underline{a}^f\left(\underline{r}^b\right)\right)\right] \underline{r}^b = G\left(\underline{a}^f(0)\right) R^b.$$

With Assumption 4, we have

$$\frac{dr^f(a)}{da} = \frac{r^2(a)\, g(a)}{G\left(\underline{a}^f(0)\right) R^b} \leq \frac{\left[R^f(a)\right]^2 g(a)}{G\left(\underline{a}^f(0)\right) R^b} \leq \frac{\beta}{1-w}.$$

so that ODE (49) indeed satisfies $r^f(a) \leq R^f(a)$, and generically the inequality is strict. This further pins down the banks strategy as Eq. (48).

Step 2 Uniqueness.

As $r^b > 0$, it is a dominant strategy for the fintech to reject borrowers if and only if $a < \underline{a}^f(0)$. In Step 1, in any equilibrium, the bank smoothly randomizes over $\left[\underline{r}^b, R^b\right]$ with a point mass at R^b. These combined with increasing $r^f(a)$ guarantee uniqueness.

Step 3 Profits.

[23] Intuitively, only when the competitor bank is not aggressive enough in equilibrium, the fintech would be hand-tied by βa from increasing its quote.

Bank profit is

$$\pi^b \quad G\left(\underline{a}^f(0)\right) R^b.$$

Fintech profit is

$$\begin{aligned}\pi^f \quad & \underbrace{\int_{\underline{a}^f(0)}^{\underline{a}^f(\underline{r}^b)} R^f(a)\, dG}_{\text{intermediate } a} + \underbrace{\int_{\underline{a}^f(\underline{r}^b)}^{\overline{a}} \left(1 - F^b\left(r^f(a)\right)\right) r^f(a)\, dG}_{\text{high } a\text{, compete with bank}} \\ \underbrace{=}_{F^b(r)=1-\frac{\underline{r}^b}{r}} & \int_{\underline{a}^f(0)}^{\underline{a}^f(\underline{r}^b)} R^f(a)\, dG + \int_{\underline{a}^f(\underline{r}^b)} \frac{\underline{r}^b}{r^f(a)} r^f(a)\, dG \\ = & \int_{\underline{a}^f(0)}^{\underline{a}^f(\underline{r}^b)} R^f(a)\, dG + \underline{r}^b\left[1 - G\left(\underline{a}^f\left(\underline{r}^b\right)\right)\right].\end{aligned}$$

The algebra also shows the conditional fintech profit for each type a.

□

7.4 Proof of Proposition 3

A full characterization of the equilibrium is as follows.

Proposition. *Suppose information cost $c = \infty$. The credit competition equilibrium is unique.*

1. *When $w < 1 - \theta$, only the fintech makes an o er $r^f = R^f(\overline{a})$ i $\mathrm{E}\left[R^f(\overline{a})\right] \geq 0$;*
2. *When $1 - \theta \leq w \leq \hat{w}$ where $r^{f,be}(\hat{w}) = R^b(\hat{w})$, only the bank makes an o er $r^b = R^b$;*
3. *When $w > \hat{w}$, the bank always makes an o er whereas the fintech randomly makes an o er with probability m^f; an o er's interest rate is randomized over common support $\left[r^{f,be}, R^b\right]$ according to CDF $F^b(r) = 1 - \frac{r^{f,be}}{r}$ and $F^f(r)$.*

Proof. Part 1) readily follows from the bank exiting $w < 1 - \theta$. For Part 2) versus Part 3), note that $R^b(w) = \frac{\theta}{1-w} - 1$ increases in w, and $r^{f,be}(w)$ decreases in w as shown from the implicit function theorem,

$$\frac{\partial r^{f,be}(w)}{\partial w} = -\frac{\frac{\partial \pi^f(r,w)}{\partial w}}{\frac{\partial \pi^f(r,w)}{\partial r}} < 0;$$

as a result, there exists $\hat{w}$ with $r^{f,be}(w) > (<)\, R^b(w)$ when $w < (>)\, \hat{w}$. Then for the case of Part 2), the fintech exits because lending incurs losses, and the monopolist bank charges R^b.

For Part 3) when $w > \hat{w}$, I first argue that the equilibrium is in well-behaved mixed strategies. Since being uninformed is a special case of information structure, the results in Theorem 1 apply. To be more specific, when making an offer, lenders randomize interest rates over common support $[\underline{r}, \overline{r}]$ according to smooth distributions, except that one lender may have a point mass at $\overline{r}$.

Then I characterize the equilibrium. In this case, $\overline{r} = R^b$ and $\underline{r} = r^{f,be}$. A lender makes the same profits when quoting any $r \quad \left[r^{f,be}, R^b\right)$. When evaluated at $r = r^{f,be}$, we have $\pi^f\left(r^{f,be}\right) = 0$

and $\pi^b\left(r^{f,be}\right) \quad r^{f,be} > 0$; so the fintech randomly makes an offer with probability m^f and the bank always makes an offer.

The bank's profit over $r \quad \left[r^{f,be}, R^b\right]$ is

$$\pi^b(r) \qquad \underbrace{(1-m_f)}_{\text{no fintech offer}} r + \underbrace{m_f}_{\text{fintech offer}} \underbrace{\left[1-F^f(r)\right]}_{Pr.\ r^f > r^b} \cdot \underbrace{\left[1-G\left(\underline{a}^f(r)\right)\right]}_{Pr.\ R^f(a) > r^b} r. \tag{50}$$

The fintech's profit is

$$\pi^f(r) \qquad \left[1-F^b(r)\right] \cdot \mathrm{E}\left[\min\left(R^f(a), r\right)\right] + \int_{\underline{r}}^{r} \int_{\underline{a}}^{\underline{a}^f(s)} R^f(a)\, dG(a)\, dF^b(s).$$

A lender's equilibrium strategy is pinned down from the competitor's indifference condition, so

$$F^b(r) = 1 - \frac{\underline{r}}{r}.$$
$$F^f(r) = 1 - \frac{\underline{r}}{r} + \frac{1-m_f}{m_f} \cdot \frac{r-\underline{r}}{\overline{G}\left(\underline{a}^f(r)\right) r},$$

where the boundary condition at $\overline{r} = R^b$ yields

$$1 - m_f = \frac{\overline{G}\left(\underline{a}^f(\underline{r})\right)\underline{r}}{\overline{G}\left(\underline{a}^f(\underline{r})\right)\underline{r} + \overline{r} - \underline{r}}.$$

□

7.5 Appendix for Section 4.3

Lemma 8. *Equilibrium information structure profile $\{P^w\}_{w \quad [0,\overline{w}]}$ corresponds to a collection of thresholds $\hat{a}_1, \hat{a}_2, \cdots \hat{a}_n$ such that in each w, the fintech chooses the optimal $\hat{a}$ among $\hat{a}_1, \hat{a}_2, \cdots \hat{a}_n$ as the lending standard.*

Proof. Since the benefit (lending profits) and cost of learning are additively separable across markets, the same argument in the proof of Theorem 1 applies in each market w: the information structure features a threshold learning, and lending profit only depends on the screening standard. Therefore, it is w.l.o.g. to find $\hat{a}_1, \hat{a}_2, \cdots \hat{a}_n$, and in each w, the fintech chooses the optimal one as screening threshold. □

For illustration purpose, I use $\hat{a}_h$ (high) and $\hat{a}_l$ (low) to denote the two potential thresholds between which the fintech considers to adopt in a generic market w.

Proof of Proposition 4

Proof. I show that as w increases, a relatively high screening standard can no longer support an equilibrium—the incentive to deviate to $\hat{a}_l$ increases with w. The fintech's net profit in the conjectured equilibrium is

$$
\begin{aligned}
Y(\hat{a}_h, w) \;\;, \;\; & \pi^f(\hat{a}_h; w) - \delta c I(\hat{a}_h)\, dw \\
& \begin{cases} (1-w)\, h(w) \cdot \int_{\hat{a}_h}^{\overline{a}} R^f(a)\, dG(a) - \delta c I(\hat{a}_h)\,, & w < 1-\theta, \\ (1-w)\, h(w) \cdot \int_{\hat{a}_h}^{\overline{a}} \min\left\{\underline{r}, R^f(a)\right\} dG(a) - \delta c I(\hat{a}_h)\,, & w \geq 1-\theta, \end{cases}
\end{aligned}
$$

where $\underline{\mathrm{r}}$ is the equilibrium lower interest rate. Then the incentive to deviate to $\hat{a}_l$ is

$$
\begin{aligned}
& Y(\hat{a}_l, w) - Y(\hat{a}_h, w) \\
& \begin{cases} (1-w)\, h(w) \cdot \int_{\hat{a}_l}^{\hat{a}_h} R^f(a)\, dG(a) - \delta c\left[I(\hat{a}_h) - I(\hat{a}_l)\right], & w < 1-\theta, \\ (1-w)\, h(w) \cdot \int_{\hat{a}_l}^{\hat{a}_h} \min\left\{\underline{r}, R^f(a)\right\} dG(a) - \delta c\left[I(\hat{a}_h) - I(\hat{a}_l)\right], & w \geq 1-\theta, \end{cases}
\end{aligned}
$$

where equilibrium price $\underline{r}$ is taken as given. Since $(1-w)\, h(w)\, R^f(a)$ increases in w, the deviation incentive increases in w. □

Expansion with History

Example 1. Suppose that the fintech currently resides in a relative poor markets $\left(\underline{w}, w_{(1)}\right)$ where a high screening standard $\hat{a}_h$ is used, and it would choose to enter new markets $\left(w_{(1)}, w_{(2)}\right)$—up until threshold market $w_{(2)} < \overline{w}$. Along with the expansion, it may acquire new information for setting a lower screening standard $\hat{a}_l$, and the new standard may be used in both the new markets and some of the existing markets. In this regard, let $\hat{w} \quad \left(\underline{w}, w_{(2)}\right)$ denote the threshold market at which the screening standard is reduced to $\hat{a}_l$ from $\hat{a}_h$. To clarify, $\hat{a}_l, w_{(2)}, \hat{w}$ are endogenous, but the Envelope Theorem allows us to focus on the direct effects when making the decision on $\hat{w}$.

The fintech's net profit when adopting an existing lending $\hat{a}$ in market w is

$$
Y(\hat{a}; w) = dw \left\{ (1-w)\, h(w) \int_{\hat{a}}^{\overline{a}} \min\left\{R^f(a), \underline{r}(\hat{a})\right\} g(a)\, da - \delta c I(\hat{a}) \right\}.
$$

where $\underline{r}(\hat{a})$ is the equilibrium lower bound of the lenders' randomized interest rates. Let $\Delta\Phi(\hat{w})$ denote the gain from expansion if the screening standard is adjusted at $\hat{w}$, given the optimal expansion $w_{(2)}$ and information acquisition $\hat{a}_l$:

$$
\Delta\Phi(\hat{w}) = \max_{\hat{a}_l, w_{(2)}} \left\{ \int_{\hat{w}}^{w_{(1)}} \left[Y(\hat{a}_l) - Y(\hat{a}_h)\right] + \int_{w_{(1)}}^{w_{(2)}} Y(\hat{a}_l) \right\}.
$$

When $\overline{w}$ is sufficiently small, the fintech does not have incentive to acquire a new threshold $\hat{a}_l$, because the potential usage of the new information is small. To see this, the incentive to adopt $\hat{a}_l$ in a specific market w is $Y(\hat{a}_l; w) - Y(\hat{a}_h; w)$, which is exactly $-\frac{\partial \Delta\Phi(w)}{\partial w}$. Given the fact that the fintech's current information structure in existing markets is optimal, there is no incentive to deviate to $\hat{a}_l$ in market $w_{(1)}^+$, or $-\frac{\partial \Delta\Phi(w)}{\partial w}\big|_{w=w_{(1)}^+} < 0$. The condition says that the fintech would like to adjust lending standard only in even wealthier markets. So if $\overline{w}$ is small, the fintech may never acquire new information and uses only one threshold $\hat{a}_h$.