Fintech Expansion*

Jing Huang

March 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

---

*Texas A&M, Mays School of Business, E-mail: jing.huang@tamu.edu. I am grateful for valuable comments from Chun Chang, Will Cong, Jason Donaldson, Zhiguo He, Chong Huang (discussant), Yueran Ma, Gregor Matvos (discussant), Simon Mayer, Shumiao Ouyang, Cecilia Parlatore, Giorgia Piacentino, Uday Rajan (discussant), Adriano Rampini, Jian Sun, Vish Viswanathan, Yiyao Wang, Yao Zeng, Anthony Lee Zhang, Leifu Zhang, Zhen Zhou, and participants at Workshop on Financial Intermediation and Regulation at Queen's University, WFA 2022, CICF 2022, U Toronto Junior Finance/Macro Conference, and seminar participants at Tsinghua SEM, Tsinghua PBC, NUS, HKU, SAIF, Cornell University, Baruch College, Southern Methodist University, UC Davis, Texas A&M University, Temple University, Indiana Kelly, and Berkeley Haas. All errors are my own.

1 Introduction

In the past decade, the global banking industry has undergone major transformation. Following the Great Recession, banks faced stricter regulations and increased competition from fintech and bigtech sectors, who provide unique front-end services and have revolutionized credit information processing using alternative data and machine learning.[1] In the U.S., they have grown rapidly, with Quicken Loans becoming the largest mortgage originator and high growth rates for business lending (43.1% annually) and Buy-Now-Pay-Later (BNPL) loans (over 100% annually).[2] The long-term effects of digital disruption remain uncertain, particularly as BigTech companies aggressively enter the lending business. This poses a significant challenge to traditional banks, potentially making their legacy technologies and branch networks obsolete.[3]

The lending of Fintechs—which encompass both fintech and bigtech players in this paper—differs from bank lending in many ways, as supported by industry practices and growing empirical evidence. For example, consider a food truck business using Square's point-of-sale system. As the payment processor, Square can predict the food truck's future revenue from payment data and seize the sales that flow through.[4] Indeed, Square offers loans that are automatically repaid through a percentage of sales, and promotes its credit screening processes as different from traditional credit scores. This can be seen on Square's offical website, and similar loan services are also available at PayPal and Amazon:

> "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 affect your credit score*."

Crucially, without alternative data like the food truck's real-time location footprints, a bank

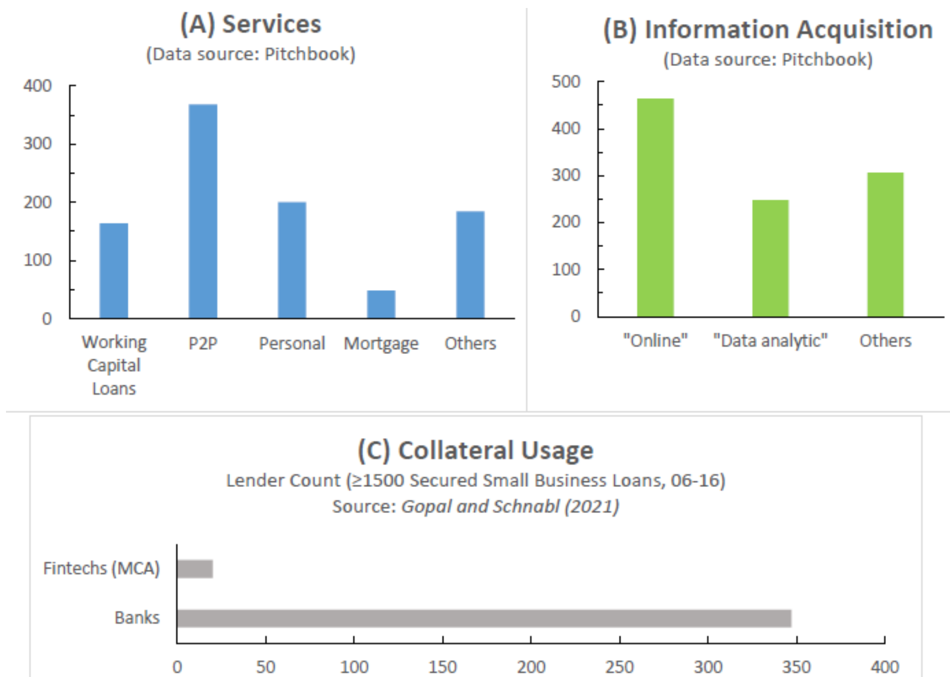
[1]See Acemoglu, Makhdoumi, Malekian, and Ozdaglar (2019). Alternative data include digital footprints (Berg, Burg, Gombović, and Puri, 2020), mobile phone logs (Agarwal, Alok, Ghosh, and Gupta, 2020), payments (Ghosh, Vallee, and Zeng, 2021) and with machine learning, they greatly improve credit predictions (Di Maggio, Ratnadiwakara, and Carmichael, 2021). Many fintechs emphasize this approach in their business descriptions (Figure 1, Panel B.)

[2]See TransUnion report in 2018. For a summary of fintech lending, see Berg, Fuster, and Puri (2021).

[3]Fintech customers have solid credit scores (Buchak, Matvos, Piskorski, and Seru, 2018; Tang, 2019; Di Maggio and Yao, 2020), suggesting that fintech lending competes or bank customers.

[4]For credit assessment based on payment data, see Parlour, Rajan, and Zhu (2021); Ghosh, Vallee, and Zeng (2021); Ouyang (2021).

Figure 1: Fintech Lenders Summary (Count)



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 (2020), and shows a small presence of fintechs—most against merchant cash advances (MCA, similar to working capital loans).

cannot predict future sales. Furthermore, even if the bank had access to this information, it would be hard to seize the food truck's cash flows. Instead, bank lending heavily relies on *physical collateral*, such as the truck in this example. As a result, when granting a loan, the fintech lender places greater importance on the borrower's latent characteristics, while the bank focuses more on the collateral quality.

Data-driven lending is prevalent among fintech lenders. Table 2 in Gopal and Schnabl (2020), partially reproduced in Panel C of Figure 1, shows that fintechs rarely use collateral: during the period of 2006-2016, among the lenders who have issued over 1500 secured small business loans, only 20 of them are fintechs, while the number is 347 for tradiditional banks. In contrast, a textual analysis of Pitchbook's company descriptions reveals that fintechs often extend their credit based on sales, invoices, and receivables (Panel A), with a strong focus on information acquisition (Panel B)—over 450 fintechs advertise digital services, and over

250 highlight algorithmic credit analysis.

This paper introduces a new framework emphasizing fintech lending as a distinct, data-based service competing with traditional collateral-based lending. Existing studies on fintech lending often use traditional bank competition models, with the fintech seen as a lender with a different screening ability,[5] or apply standard industrial organization (IO) frameworks to capture heterogeneous lending services in a reduced-form way (see, Buchak, Matvos, Piskorski, and Seru, 2018). However, unresolved issues remain: For example, there is mixed evidence on equilibrium prices upon fintech entry, and both fintech and bank lending seem to serve specific borrowers better while still competing with each other. With an emphasis that the fintech provides different lending services, this paper aims to offer fresh insights into these issues and the implications on fintech disruption.

In my model, borrowers differ in own funds w and *private* productivity a. They finance their investment shortfall $1 - w$ through debt to generate cash flow a. Initial wealth w represents the observable credit quality (LTV) and indexes distinct markets where lenders compete, while productivity a is the latent quality. Two lenders—a bank and a fintech—simultaneously choose whether to make an offer and the corresponding interest rate. The key friction is *limited enforcement*, meaning that borrowers can abscond with amounts beyond the lender's enforcement capabilities. Borrowers compare the *effective cost of borrowing* from different lenders and choose the cheaper one.

Bank and fintech lending fundamentally differ in their enforcement technologies, which result in their different evaluations of the same borrower. In other words, I study a "private value" setting distinct from the common value framework in previous theories. Specifically, the bank cannot seize cash flow a, and enforces loans by collateralizing the capital.[6] For the bank, borrower quality depends solely on initial wealth (LTV). The bank exits low-wealth markets in the spirit of Holmstrom and Tirole (1997), and otherwise offers interest rates subject to the standard collateral constraint. In contrast, the fintech can seize a fraction of future cash flows thanks to its front-end service, but does not take physical collateral due to a lack of personnel. As a result, the fintech values borrowers with high productivity which

[5] Thus fintechs and banks essentially offer the same lending service, but with different information precision and funding costs. See, for instance, Hau, Huang, Shan, and Sheng (2019); He, Huang, and Zhou (2023); Chu and Wei (2021); Biancini and Verdier (2019)

[6] See Hart and Moore (1994); Hart (1995); Kiyotaki and Moore (1997); Kehoe and Levine (1993); Rampini and Viswanathan (2010); Lian and Ma (2021) (for small businesses) , among others.

substitutes for LTV quality.

Fintech lending features powerful information technology. While the front-end enforcement enables a novel way to channel funds to households and small businesses of high latent qualities, future cash flows are the borrowers' private information. Hence, the fintech faces adverse selection as low-productivity borrowers prefer defaulting with the fintech over secured lending with the bank. However, the fintech benefits from recent revolutions of machine learning, big data, and more. In the model, the fintech can secretly learn about *any partition* of borrower productivity at entropy costs, allowing it to categorize borrowers as desired and offer (potentially) tailored quotes. Additionally, big data facilitates cross-market predictability, allowing fintechs to use accumulated data in existing markets to develop predictive models for their expansion to new markets. Consistent with confidential algorithms in practice, information acquisition by the fintech is *unobservable* to the bank.

My model is best suited for fintech lending to small businesses based on future cash flows, like Square. The insights, nevertheless, apply to a broad range of fintech lending, with an adapted interpretation of the latent quality. For fintechs offering unique services, there is an effective exclusion threat, and the latent quality represents the borrower's willingness to repay to maintain future access. Examples include Alibaba Group's small merchant platform, fast and flexible loans for contingency needs, and "Buy Now Pay Later" services.[7] Furthermore, for lending with such specific "scenarios," monitoring loan usage is easier, which is translated to ex ante fintech enforcement ability in my model without monitoring.

The main result of my model 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 to steal the bank's customers. Credit competition equilibrium is in mixed strategy, with both lenders making positive profits. The coarse learning result is driven by competition and debt contracts. The fintech does not benefit from extra information (beyond the lending threshold) because it won't adjust its equilibrium quotes. Suppose in equilibrium, the fintech secretly knows the borrower's true productivity. First, the fintech is indifferent across any relatively low quotes that the borrower would fully repay, because equilibrium bank competition is so fierce that within this region a higher quote is offset

[7] 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.

with a lower chance of winning the customer. Second, across any higher quotes incurring borrower default, the fintech is indifferent either, because now the payoff relevant rate is the enforceable amount rather than the quote itself. Last, the fintech is indifferent between these two regions that share the same knife-edge quote. Therefore, additional information does not affect the fintech's strategy.

Fundamentally, the "coarse" learning result is due to different lending technologies. The bank only reacts to the fintech's quote itself, ignoring any information about productivity implied by the quote because it relies on collateral. 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. According to my model, unsecured lending is "coarse" because the competition from the secured lending option eliminates information rent. As a testable implication, in response to the competition environment, unsophisticated interest rates would be offered at loan origination, while fees may be customized after the loan is granted.

The credit market equilibrium displays lender specialization, with traditional credit access depending on observable credit qualities like low LTV, while fintech lending targets borrowers with high latent qualities. The fintech's front-end services enable innovative enforcement well-suited for high-productivity borrowers, and the information technology serves to more effectively target these customers. This 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 accessing bank credit enjoy lower interest rate due to competition. When the "latent quality" is interpreted as the preference for fintech service, my model aligns well with empirical evidence, as shown in Di Maggio and Yao (2020) where fintech consumers have different spending habits, and Buchak, Matvos, Piskorski, and Seru (2018) where fintechs specialize in mortgage refinancing.

My model has unique implications for fintech disruption. Canonical "common value" competition theories predict negative impacts on traditional lending, as fintechs with better information technology would eliminate traditional lending's information rent. However, my paper emphasizes that fintech lending competes on a different dimension, and delivers more nuanced impacts depending on the specific fintech technologies we talk about. Better "enforcement" technology hurts traditional lending, but better "information" technology can benefit it. Enforcement essentially shapes the fintech's distinct lending service, so reduced enforcement friction weakens differentiation and intensifies competition. On the other hand, lower information costs enable the fintech to better identify high-productivity customers, leading to a more efficient separation of borrowers and less intense competition. In the long run, both lending services are likely to coexist and compete. Traditional banks may have limited incentives to aggressively fight back, as they still maintain some rent and implementing similar front-end infrastructure can be costly.

In the last part of my paper, I argue that big data technology significantly reduces information costs through out-of-market predictability, allowing the fintech lender to utilize early-stage data from unbanked markets to expand into wealthy markets. The fintech industry initially faces limited data and high information costs, and only profits by issuing high-interest, risky loans to unbanked populations. Without big data, the fintech would have to independently acquire information for each market through trial and error, facing severe adverse selection where traditional lending is present. However, big data technology transforms traditionally "soft" information about latent characteristics into "hard" data, allowing for out-of-market predictability. As a result, data collected from early-stage operations in unbanked markets can be used to develop predictive models to identify high-quality borrowers in wealthy market, thus facilitating expansion.

Related Literature

The paper connects with several strands of literature. It contributes to the *growing fintech literature* and the *banking IO literature*. The *limited enforcement* friction borrows from the *incomplete contracts literature* (Hart and Moore, 1994; Hart, 1995), and fintechs provide financing solutions alternative to collateralized lending (Kiyotaki and Moore, 1997; Kehoe and Levine, 1993; Rampini and Viswanathan, 2010). The novel framework complements the *canonical credit competition theories* (Broecker, 1990; Hauswald and Marquez, 2003) to understand credit market implications.

My paper's emphasis on fintechs' distinct lending technologies and differentiated competition aligns with the growing empirical evidence on alternative lending.[8] This literature often documents that fintech lenders provide technology-based services and meanwhile collect data (Ouyang, 2021; Liu, Lu, and Xiong, 2022), which exemplifies fintech lending in my paper as a combination of service-enabled enforcement and information. In addition, fintechs compete for bank customers in various markets such as P2P lending (Tang, 2019; De Roure, Pelizzon, and Thakor, 2022), consumer loans (Di Maggio and Yao, 2020), and small business loans (Balyuk, Berger, and Hackney, 2020).[9]

Fintech lending is information-driven.[10] Closest to my paper, and related to open banking that makes financial data accessible to fintechs under customer control (He, Huang, and Zhou, 2023; Goldstein, Huang, and Yang, 2022; Babina, Buchak, and Gornall, 2022), Ghosh, Vallee, and Zeng (2021) demonstrate a synergy between payment data and fintech credit extension, and Gambacorta, Huang, Li, Qiu, and Chen (2020) find that bigtech credit strongly reacts to changes in firm characteristics instead of house prices, so its lending relies on data rather than collateral.

On the theory side, my framework complements *canonical credit competition models* (for a brief review, see Gorton and Winton, 2003) that are applications of the *common value auction* (Milgrom and Weber, 1982; Hausch, 1987; Kagel and Levin, 1999; Banerjee, 2005) to understand credit market outcomes. In this literature, the central friction is that borrowers privately know their credit types (Stiglitz and Weiss, 1981), and lenders care about the credit quality *equally*—which is the key difference from my paper. In classic frameworks of Broecker (1990), Hauswald and Marquez (2003), when lenders are asymmetrically informed, the "winner's curse" arises as competitors are worried about picking up lemons, resulting in rent to better informed lenders (Sharpe, 1990).[11] Lenders may also require collateral to

[8]Featuring digital front-end services, fintechs are faster and more efficient (Fuster, Plosser, Schnabl, and Vickery, 2019), and are better at certain services such as mortgage refinancing (Buchak, Matvos, Piskorski, and Seru, 2018) and BNPL loans (Di Maggio, Williams, and Katz, 2022). For surveys of digital disruption in banking, see Berg, Fuster, and Puri (2021); Allen, Gu, and Jagtiani (2020); Vives (2019).

[9]My paper only looks at credit competition for loans on the asset side. Recent evidence during the COVID-19 pandemic (Ben-David, Johnson, and Stulz, 2021; Bao and Huang, 2021; Cumming, Martinez Salgueiro, Reardon, and Sewaid, 2020) suggests a need for a framework that incorporates the funding differences between fintechs (securitization) and banks (stable deposits).

[10]Even basic digital footprints perform as well as credit scores (Berg, Burg, Gombović, and Puri, 2020), and can outperform bank predictions when combined with machine learning (Di Maggio, Ratnadiwakara, and Carmichael, 2021) that are better than human judgement (Jansen, Nguyen, and Shams, 2021), let alone the transactions data (Square) or when customers "live there lives" on its App (Liu, Lu, and Xiong, 2022).

[11]More broadly, credit competition is important for studying capital requirements (e.g., Thakor, 1996),

recover loss (Dell'Ariccia and Marquez, 2006), which also serves as a screening device for borrower type (Besanko and Thakor, 1987). However, collateral is costly due to inefficient liquidation, and Boot and Thakor (1994); Petersen and Rajan (1994); Berger and Udell (1995) show collateral requirements fall as lender information improves; closest to this paper is Sengupta (2007) showing the less informed entrants use collateral in credit competition. In my paper, collateral serves to enforce and so inefficient liquidation never occurs; collateral and information-based lending are different services that suit different customers, with no clear superiority of one over the other. In addition, my main theoretical result is "coarse" information acquisition. The new information technology that transforms "soft" information into "hard" data is disruptive to especially *relationship banking* (Rajan, 1992).

The theory literature on fintech lending is new. Parlour, Rajan, and Zhu (2021) emphasize that customers' payment services provide information about their credit qualities, and therefore the fintech competition in payment services disrupts this natural information spillover within the traditional bank. The welfare implications of open banking regulation are studied by He, Huang, and Zhou (2023), while Goldstein, Huang, and Yang (2022) evaluate this policy by considering the endogenous responses from bank's deposit funding (liability side) to bank's loan making (asset side). Vives and Ye (2021) examine how the diffusion of information technology affects lending competition and the welfare implications.

2 The Model

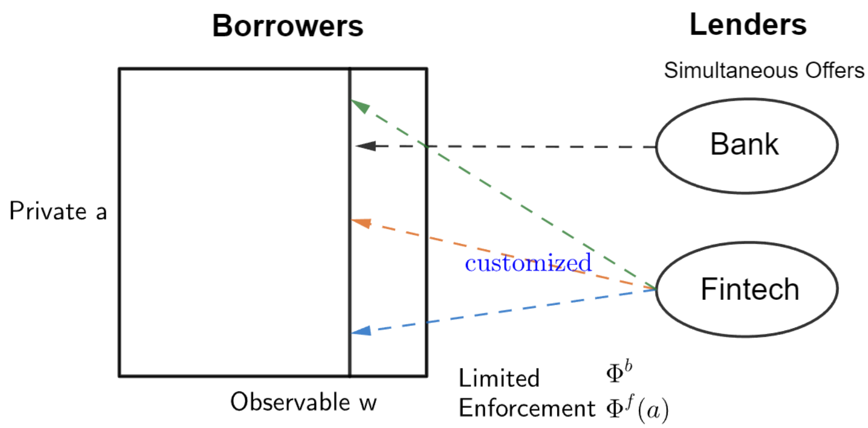
We present the main model and explain the key differences from the canonical frameworks.

2.1 Model Setup

Figure 2 summarizes the model. The economy lasts for one period and consists of three types of risk-neutral agents. A bank and a fintech compete by making simultaneous loan offers to borrowers.The key friction is *limited enforcement*: a borrower walks away from promised repayment whenever she could. To enforcement repayment, the traditional bank collateralizes the physical capital, while the fintech can collect up to a fraction of sales. In

information dispersion (e.g., Marquez, 2002), credit allocation (e.g., Dell'Ariccia and Marquez, 2004, 2006) and others.

Figure 2: Model Scheme



addition, the fintech is able to flexibly acquire information to give customized offers.

2.1.1 Borrowers

At $t = 0$, each borrower has one project that costs one dollar to install, but she only has $w \in [0, 1]$ at hand and thus needs to finance the shortfall $1 - w$.[12] We assume that borrowers enjoy sufficiently large private benefit from their projects, so that they always want to borrow and produce.[13] 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 contributed by the borrower herself is observable and captures the loan-to-value (LTV) ratio.[14] In contrast, productivity a is the borrower's private information at $t = 0$, which becomes publicly known at $t = 1$. As we explain in detail shortly, the fintech lender, but not the bank, is able to flexibly learn about a before making the loan at $t = 0$. Henceforth, I call each w a market, which consists of a pool of borrowers with different underlying qualities but the same LTV.

Let the CDF $G(a\,|w)$ and PDF $g(a\,|w)$ summarize the prior distribution of productivity a over $[\underline{a}, \overline{a}]$ in market w. The distribution of markets $w \in [0, \overline{w}]$ for $\overline{w} \leq 1$ is characterized

[12] 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.

[13] Endogenous borrower participation only complicates our analysis of competition between lending technologies without adding much more insights.

[14] First, the analysis is robust to multiple projects as long as there is no signaling through investment size. Second, loan demand could be separated from loan size by varying the population (measure) of w.

by CDF $H(w)$ and PDF $h(w)$. The baseline model considers competition within a market w. Model extension (Section 4) introduces cross-market predictability, where independence between w and a is implicitly assumed.

Limited enforcement Limited enforcement is a key friction of the paper, and it is particularly relevant for the application of alternative lending, which mainly serves households and small businesses. Specifically, after a borrower takes out a loan with an interest rate r^j from lender $j \in \{b(\text{ank}), f(\text{intech})\}$ at $t = 0$, she walks away from the promised repayment whenever she could at $t = 1$.

Lender j's enforcement technology is denoted by Φ^j, which represents the maximum amount that lender j can seize. We will explain Φ^j in more detail in Section 2.1.2. The resulting *actual* repayment to quoted rate r^j 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 to cover their debt obligations, i.e. $\underline{a} \geq \Phi^j$.

Limited enforcement is a key feature that distinguishes my framework from previous models. From the borrower's perspective, the actual repayment to the lender in Eq. (1) is her *effective cost of borrowing*. When the borrower receives quotes from both the bank r^b and the fintech r^f, she selects the one with the lower effective cost:[15]

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

As the other side of the same coin, lender j is then unwilling to lend more than $\mathbb{E}\left(\Phi^j\right)$. Limited enforcement thus constrains the ex ante borrowing capacities, implying that lenders engage in price competition under asymmetric capacities from different enforcement.

Hence, in contrast with the canonical credit competition models (Broecker, 1990; Hauswald and Marquez, 2003) that are applications of common value auction, this paper features a

[15] Upon ties, she randomly chooses the lender, each with probability $\frac{1}{2}$, although the details of the tie-breaking rule do not matter because ties do not occur on equilibrium.

"private value" setting where lenders with different enforcement technologies value the same borrower differently. The model also differs from monopolistic competition models with differentiated goods, such as the Hotelling model, where customers are willing to *pay a premium* for their preference. In this paper, the borrower views the two financing options as *fungible*, and thus the "suitability" of financing options are capacity constraints of lender competition.

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 investing in data through front-end services.[16] Consider the example of a food truck. Square offers innovative business loans that are automatically repaid by a percentage of food truck sales that flow through the payment processor, and similar loans are available from PayPal and Amazon.[17] On the other hand, it would be difficult for a traditional bank to predict a food truck's future sales without alternative data such as real-time location information. Furthermore, even if the bank could learn this information, it would be unable to seize the food truck's cash flows. In contrast, the bank lends via collateralizing the physical collateral, which would be the truck in this example. As evidence for such lending pattern, Gambacorta, Huang, Li, Qiu, and Chen (2020) show that the Alipay credit correlates with firm characteristics rather than the local housing price (which represents the collateral value).

This abstraction applies to a wide range of fintech lending. Fintechs offering unique services, such as Alibaba's small merchant platform, and the "Buy Now Pay Later", enforce via an effective exclusion threat, and the borrowers' unobservable type a corresponds to their willingness to repay to maintain future access. For fintech lending tied to certain "scenarios", the latent type a represents whether the borrower's uses the loan for its intended purpose.

2.1.2 Lenders

There are two lenders, a bank and a fintech,[18] both with unlimited funding at unit cost. Lending is restricted to standard debt contracts. After the fintech lender acquires information

[16] Lian and Ma (2021) document earning-based lending for *large* corporations. In their sub-sample of small firms of Compustat—still larger than firms in this paper, bank lending is prominently collateral-based.

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

[18] This assumption allows me to focus on competition between two technologies, and the one fintech setting is needed to study its expansion across markets in Section 4.

on productivity a (to be explained shortly), 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 in bank lending follows Hart and Moore (1994) and Kiyotaki and Moore (1997): borrowers can abscond with cash but not physical capital. Hence, the bank collateralizes the project capital, and its liquidation value to the bank is denoted by $\theta \in (0, 1)$ and publicly known. The maximum repayment that the bank can enforce is

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

To see this, suppose the borrower takes out a collateralized loan from the bank at interest rate $r^b(w)$, meaning that the bank can liquidate the collateral and get θ if the borrower defaults and repays less. Then right before paying $r^b(w)$, the borrower can renegotiate the payment down to the bank's reservation value of θ (due to inalienbility of human capital, the borrower has all the bargaining power). To focus on the enforcement friction, recall the paper assumes that a borrower always has enough resource for repayment, i.e., $\underline{a} \geq \theta$, so inefficient liquidation never occurs in equilibrium.

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

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

Hence, bank loans are always *riskless* since there is no uncertainty in the collateral value θ. Moreover, the bank lends if and only if $\theta \geq 1 - w$ when the collateral value covers the loan, so borrowers with lower w become "unbanked." Formally, denote by $m^b(w)$ the probability that the bank makes an offer, and then $m^b(w) = 1$ when $w \geq 1 - \theta$ and $m^b(w) = 0$ otherwise.

To emphasize collateralized lending, I assume that the bank cannot acquire information about borrower productivity a. Because the bank cannot seize cash flows, this information has *no fundamental value* anyway. In practice, a may have fundamental value to the bank, for example if it correlates with the collateral value, or if the bank has some bargaining power to leverage the fact that more productive borrowers are less willing to lose capital. Since canonical credit competition models (Broecker, 1990; Hauswald and Marquez, 2003) carefully examined the case where loan quality is solely determined by borrower productivity for all lenders, my paper focuses on the opposite extreme scenario where bank loan quality only depends on the collateral value θ and LTV.

To summarize the bank's strategy, if and only if $w \geq 1-\theta$, the banks makes an offer $r^b(w)$ 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.

Fintech The fintech lender in my model represents a variety of alternative lenders with similar business models, including fintechs, bigtechs, platforms, and more. I assume that the fintech does not collateralize the physical capital, which is consistent with the small fintech presence in secured small business lending (Gopal and Schnabl, 2020) and the fintech's light personnel in practice. As a key feature of my model, the fintech lender can seize a fraction $\beta \in (0,1]$ of the borrower's $t=1$ cash flow a thanks to its front-end services. For example, Square as a payment processor collects repayments by taking a fixed percentage (β) of the incoming sales (a) that flow through until the balance 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 interest rate $r^f(w)$ is

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

Based on the comparison of the two terms, it is convenient to introduce

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

as the maximum fintech quote that a type (w, a) borrower would fully repay. Relatedly, let

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

represent the lowest type of borrower who fully repays a given fintech quote of r.

In practice, some fintechs have the advantage to directly seize cash flows.[19] For fintechs that enforce via an exclusion threat, Eq. (7) also applies. In this case, the latent quality a represents the borrower's preference of the fintech's services and her willingness to repay in order to maintain access. For example, a merchant is willing to repay Alipay credit to maintain access to Alibaba's merchant platform, because it is less productive and generates only $(1-\beta)a$ elsewhere. The fintech lender controlling platform access has all the bargaining power in renegotiation, and can extract up to βa from the borrower.

Facing unknown future cash flows, fintech lending uses powerful information technology. I focus on information acquisition that results in partitions: At $t = 0$, the fintech lender *secretly* chooses a partition

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

about borrower productivity a in market w at Shannon entropy cost, which measures the "quantity of information." A partition divides a set into disjoint events ($A^i \cap A^{i'} = \emptyset$ for any $A^i \neq A^{i'}$), and the union of these events is the entire set ($\bigcup_{A^i \in \mathcal{P}} A^i = [\underline{a}, \overline{a}]$). For example, a partition $\{[0.3, 0.4) \bigcup [0.6, 1], [0.4, 0.6)\}$ (for $a \in [0.3, 1]$) allows the fintech to identify whether the borrower's productivity is between 0.4 and 0.6. Therefore the fintech lender can privately categorize borrowers' productivity in an arbitrary way and learn which category A^i the borrower belongs to; the paper thus loosely uses A^i to indicate the fintech's signal. The information technology represented by partitions well captures the decision tree models used in machine learning (see Bryzgalova, Pelger, and Zhu, 2021), and allows for sufficiently granular information structure.

Information acquisition allows the fintech lender to customize lending strategies. For each event $A^i\left(w\right) \in \mathcal{P}^w$, the fintech chooses the probability to make an offer, denoted by $m^f(A^i; w)$, and the distribution of its interest rate $F^f\left(r^f \left|A^i\left(w\right); w\right.\right)$ upon offering. It prefers borrowers of high productivity and low financing needs, but the actual participation m^f is endogenously determined in the credit competition. As the information acquisition is unobservable, the equilibrium condition requires that the fintech does not have a profitable

[19]For payment firms, the cash flows are "in processing" and have not yet arrived at the bank account; once they arrived, court ruling would be needed to seize the cash for the protection of other creditors. This also explains the difficulty for the traditional bank to seize cash flows. Moreover, fintechs closely monitor account activities and use covenants to reduce a borrower's potential diversion to other payment methods.

double deviation by secretly adjusting information acquisition to change its lending strategy.

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

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

Additionally, let c parameterize the difficulty to acquire information in general, and the cost of acquiring $\mathcal{P}^{w}$ in market w is thus

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

The total information costs for all markets is then $\int_{w} C\left(\mathcal{P}^{w},w\right)$.

Section 4 introduces cross-market predictability: the fintech lender is able to develop an algorithmic model $\mathcal{P}^{w}$ in an *existing* market w and use it to assess another market $w' \neq w$ and identify the same categorical traits as in $\mathcal{P}^{w}$. In this scenario, the cost of using an established algorithm $\mathcal{P}^{w}$ in a new market w' is reduced to

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

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

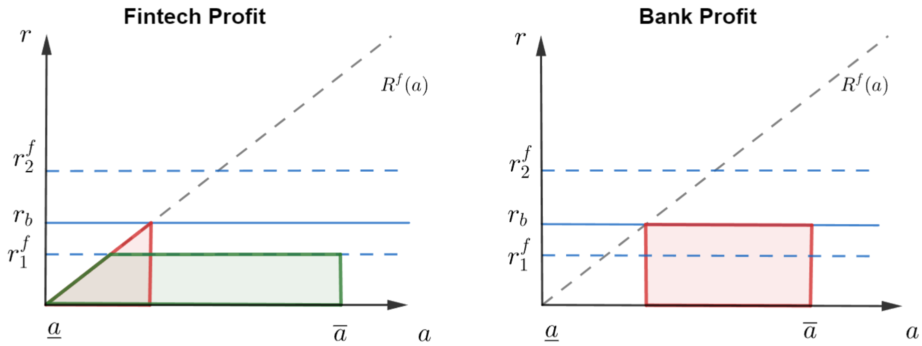
2.2 Lender Payoffs

I start with the borrower choice of the lower effective cost 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 line $R^{f}(a) \equiv \frac{\beta a}{1-w} - 1$ (Eq. 8) is the

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).

maximum repayment that the fintech can enforce 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 green area shows lender profits, with the fintech profit in the left panel and bank profit in the right panel (which is zero because nobody chooses the bank). There are two regions of actual repayment in fintech profits: borrowers with low productivity ($R(a) < r_1^f$) default and repays $R(a)$ while others repay r_1^f.

In the second case where the bank quote is lower $r^b < r_2^f$, whoever chooses the fintech's offer 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, 2020). This feature is also an important departure from canonical models where all lenders are subject to adverse selection under the "common value" setting, and the winner's curse arises when competitors have private information.

In any market $w \geq 1-\theta$, given the fintech's information acquisition $\mathcal{P}^w$ and lending strategies $\left\{m^f\left(A^i; w\right), F^f\left(r^f \left| A^i\left(w\right); w\right.\right)\right\}_{A^i \in \mathcal{P}^w}$, the bank's profit when quoting $r^b \leq R^b\left(w\right)$ is

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

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 information structure $\mathcal{P}^w$ and its customized lending strategies upon each $A^i(w)$. The bank faces competition when the fintech makes an offer, which occurs with probability m^f. In this case, a borrower chooses the bank's offer when two conditions are both met, which is also illustrated in the right panel of Figure 3: first, the bank wins the quote competition $r^b<r^f$, which occurs with probability $1-F^f\left(r^b\right)$; second, 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).

Similarly for the fintech lender, given A^i and the competitor bank's lending strategy $F^b\left(r^b;w\right)$, its expected profits when quoting r^f is

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

As illustrated in left panel of Figure 3, if $r^f<r^b$, the borrower chooses the fintech for sure; if $r^f\geq r^b$, only borrowers with relatively low productivity a chooses fintech.

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

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

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

2.3 Comparison with Literature

Let me pause to discuss how the productivity, and its information, affects the credit market competition in my model. The information regarding productivity a is more relevant to the fintech as it determines the fintech's enforceable repayments or customer quality, but this information reveals nothing about the customer quality from the perspective of a bank who values collateral only. Therefore 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 these existing models, lenders offer the same product, and lenders value the information about the borrower's creditworthiness in the same way. Even in the presence of lender affinity (for example, preference for a bank that is located nearby as in Vives and Ye (2021), or fintech affinity due to its convenience modeled in He, Huang, and Zhou (2023)), lender competition still falls in the framework of common value auction, with the necessary adjustment due to inelastic substitutability between two options. In contrast, I highlight *lenders* have different preferred borrower types due to different lending technologies, but the financing options are perfectly *fungible to borrowers*. As emphasized in Section 3.3, my model generates unique predictions that are consistent with certain empirical evidence: While in existing models less asymmetric information technology strengthens competition, an improved information technology in fintech lenders may instead weaken competition in my model.

2.4 Parameter Assumptions

I make the following assumptions throughout the paper.

Assumption 1. *The analysis focuses on the more interesting cases*

1. *$\underline{a}$ is relatively low with $R^f(\underline{a}; \overline{w}) < 0$, so that the fintech suffers from "adverse selection."*
2. *$\mathbb{E}\left(R^f(a); 1-\theta\right) > 0$, 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., virtual valuation $a - \frac{1-G(a)}{g(a)}$ weakly increases.*

The following assumption avoids abnormal information cost functions or cross-market profit patterns driven by the distributions of a and w, we make the following assumption.

Assumption 3. *Function $\log \frac{G(a)}{1-G(a)}$ is concave (convex) when $a < (>) a^{med}$; $\frac{\partial\left[(1-w)h(w)\min\left\{r,R^f(a)\right\}\right]}{\partial w}$ share the same sign with $\frac{\partial \min\left\{r,R^f(a)\right\}}{\partial w}$.*

3 Information Acquisition and Fintech Disruption

In this section, I analyze the baseline model where information is acquired independently for each market, with no inter-market predictability. The equilibrium provides insight into the full landscape of fintech disruption across borrowers with different observable risks. 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, highlighting the theme of credit competition between different lending services, I show that as information technology improves and the fintech lender becomes stronger, the competitor bank's profits may increase.

3.1 Equilibrium Definition

As explained, the fintech lender's strategy profile includes information acquisition strategy $\mathcal{P}^{f,w}$ and lending strategy $\left\{m^f\left(A^i\right), F^f\left(r^f\left|A^i\right.\right)\right\}_{A^i\in\mathcal{P}^{f,w}}$, 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. Consider a market with $w \geq 1-\theta$. In a credit market competitive equilibrium with mixed strategies, 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

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

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

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

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

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

The equilibrium presented in Definition 1, which involves two actively competing lenders, is more complex than that in Definition 2, which concerns a monopolistic fintech. Specifically, when $w \geq 1 - \theta$, the equilibrium involves mixed strategies with m^f, $F^f(r)$, and $F^b(r)$, such that any lender is indifferent across all interest rate quotes (plus not making an offer in the case of fintech if $m^f \in (0, 1)$) on the support. Under Assumption 2, the equilibrium is well-behaved: lenders randomize over interval supports $[\underline{r}^j, \overline{r}^j]$ according to a smooth distribution, except that one lender may have a point mass on the boundary.

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).

3.2 Optimal Learning: Screen Out

Generally speaking, information allows the fintech lender to customize lending, by rejecting risky borrowers and extracting rent from high-quality borrowers through price discrimination. Price discrimination seems particularly attractive to the fintech, who could *secretly* acquire more granular information to undercut the competitor bank for the right customers at the right price. However, the main finding of this paper, as demonstrated in Theorem 1, is that the optimal fintech learning strategy is surprisingly "coarse" and involves only 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 cutoff* $\hat{a}$*:*

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

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

1. *When* $w \geq 1-\theta$*, 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* $\left[\underline{r}, R^b \right]$ *according to*

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

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

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 offers* $r^f = R^f(\overline{a})$ *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 two core forces behind the simple single-threshold structure for the fintech's optimal screening within its equilibrium strategy. Consider the more intriguing case of $w \geq 1-\theta$ where a competing bank is present, and say that $a > \hat{a}$ so that the fintech makes loan offers. In this scenario, acquiring additional information about a can benefit the fintech in two ways: customizing pricing, and indirectly revealing the competitor bank's strategy. Under my "private value" setting, it is clear that this second inference effect on competitor's strategy is absent.

Even more surprisingly, I show that the first direct effect is also absent: in equilibrium, the fintech gains no advantage from knowing borrower quality a. To see this, when facing the bank's equilibrium strategy, the fintech's profits when quoting any r^f is[20]

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

which includes two possible scenarios depending on whether the borrower with productivity a defaults (the first term) or not (the second term). The green area in Figure 3 illustrates Eq. (23) when the bank rate is *realized* as $r^b > r^f = r^f_1$, with two parts of a.

With Eq. (23), I show that even if the fintech knows the borrower type a exactly, it is *indifferent* with any interest rate quote $\tilde{r}^f \in \left[\underline{r}, R^b\right)$; hence "information" about a has no value to the fintech because its optimal strategy remains the same regardless of this knowledge. Consider the fintech's deviation payoff when it knows type a and varies the potential quote $\tilde{r}^f$. The potential quote $\tilde{r}^f$ 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 the debt contract extracts βa ex post (analogous to the first term of Eq. (23)). Then any quote in this region $\tilde{r}^f \geq R^f(a)$ becomes irrelevant, leading 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

[20]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 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.

any quotes within the intersection of this region $\tilde{r}^f \leq R^f(a)$ and $[\underline{r}, R^b]$;[21] so competition essentially eliminates the potential advantage of a customized offer in this region. Last, as the knife-edge case quote $\tilde{r}^f = R^f(a)$ falls into both regions of quotes where the fintech is indifferent, there is no need to distinguish between these two regions. Therefore, the fintech, even with the knowledge of a, remains indifferent across any quote on the original equilibrium support $[\underline{r}, R^b]$, showing no incentive to learn any additional information within $a > \hat{a}$.

Finally, in the case where the fintech is a monopolist, the same logic as in the "default" scenario applies, leading to coarse learning. By charging the highest rate $R^f(\overline{a})$ and letting all borrowers default, the fintech extracts βa ex post and effectively price discriminates its customers. In sum, given the bank's equilibrium strategy, information beyond $\hat{a}$ has no benefit for the fintech.

Different services in competition is the fundamental force that drives the result. As explained, the latent type a has no fundamental value to the bank who cannot seize cash flows. Hence, when competing with the fintech, the bank only reacts to the fintech's *interest rate quote itself*, cutting its own rate when the fintech's quote is high, regardless of any information implied by this quote. The resulting equilibrium bank strategy as in Eq. (20) thus removes any incentive for the fintech to even *secretly* learn about a to customize pricing.

Uniqueness of equilibrium We now explain the uniqueness of the equilibrium in two steps. First, without bank's strategic response to the fintech's customized pricing, any equilibrium information structure must be two intervals. Suppose there is another potential equilibrium with a finer information structure for the fintech. However, the bank's equilibrium strategy is still in the form of Eq. (20) since it only reacts to the equilibrium interest rate level, which is captured by $\underline{r}$. (This particular result will be illustrated shortly in the benchmark case of a perfectly informed fintech.) Hence, a finer information structure cannot be supported in an equilibrium because the fintech would like to deviate to a less costly two-interval structure and achieve the same lending profits.

Second, given the threshold structure, the optimal screening threshold is unique. Under Assumption 3, the marginal cost of information as a function of $\hat{a}$ exhibits desirable curvature properties. In this situation, Eq. (22) determines at most one local maximum that only

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

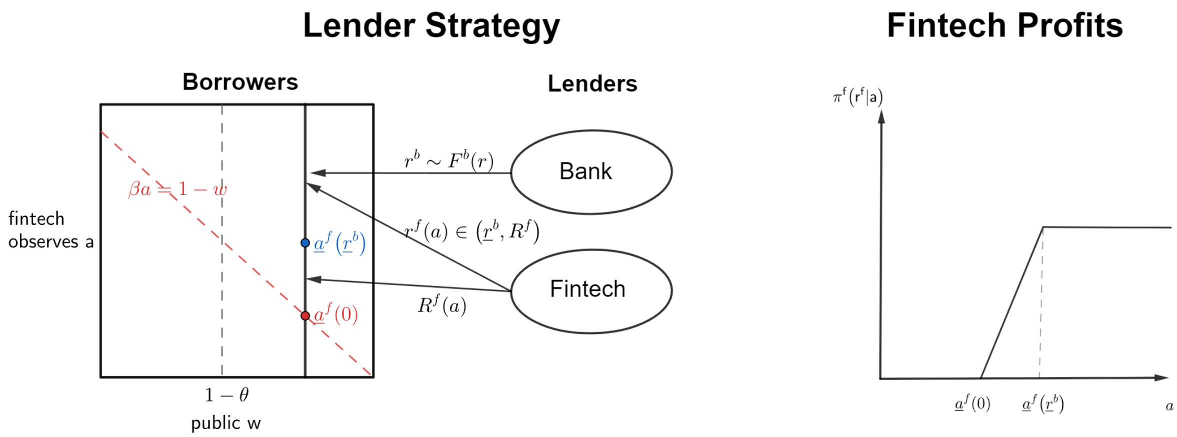


Figure 4: Fintech Perfectly Observes a

arises when the information cost c is sufficiently small; this local maximum corresponds to the unique screening threshold if the fintech acquires information (interior solution).

Perfect information benchmark To further illustrate the limited value of information, I now present a benchmark setting where the fintech is endowed with perfect information about productivity a (or learning is "free"). Since there is no uncertainty, I focus on riskless fintech loans with quotes $r^f(a) \leq R^f(a)$ (similar in spirit to riskless bank loans). The equilibrium is characterized in Online Appendix 7.2, and the left panel of Figure 4 provides an illustration.

In this equilibrium, the fintech uses a pure strategy: It rejects unprofitable borrowers with $\beta a < 1 - w$, or equivalently $a < \underline{a}^f(0)$, and offers a customized interest rate $r^f(a)$ to the remaining borrowers. The bank's equilibrium strategy is the limiting case of Theorem 1 with $c \to 0$: it makes an offer with interest rate that is randomized over $\left[\underline{r}^b, R^b\right]$ according to the following CDF,

$$F^b(r) = 1 - \frac{\underline{r}^b}{r}, \text{ with } \underline{r}^b = \frac{G\left(\underline{a}^f(0)\right) R^b}{G\left(\underline{a}^f(0)\right) + 1 - G\left(\underline{a}^f\left(\underline{r}^b\right)\right)}.$$

Similar to Varian (1980), the bank uses a mixed strategy as it cannot identify its captured borrowers $a < \underline{a}^f(0)$ who are rejected by the fintech. For borrowers with $a \geq \underline{a}^f\left(\underline{r}^b\right)$, two lenders are competing, which corresponds to the second term in Eq. (23). The bank's strategy $F^b(r)$ highlights the fact that it only reacts to the fintech's lending threshold $\hat{a} =$

$\underline{a}^f(0)$ (which determines $\underline{r}^b$), rather than any further information beyond this threshold. To see this, even if the bank infers from competition the type of the marginal customer, it is indifferent about the type a itself due to the same collateral value for all borrowers. This "private value" setting essentially eliminates the fintech's information rent in competition, leading to aggressive bidding from the bank in equilibrium. As shown in the right panel of Figure 4, the fintech lender earns a constant rent for borrowers with $a \geq \underline{a}^f\left(\underline{r}^b\right)$, despite making a perfectly customized offer $r^f(a)$ to undercut the bank.

Borrowers with $\underline{a}^f(0) \leq a < \underline{a}^f\left(\underline{r}^b\right)$ always prefer the fintech loan over the bank loan for its lower *effective cost*. This region corresponds to the first term in Eq. (23) with $1 - F^b\left(R^f(a)\right) = 1$, and the fintech can extract the full rent via price discrimination by setting $r^f(a) = R^f(a)$ for these borrowers. However, with the *debt contract*, the fintech can still achieve the same payoff by effectively price discriminating ex post, without knowing the borrower's type ex ante. Specifically, by issuing risky loans that charge $r^f \geq R^f\left(\underline{a}^f\left(\underline{r}^b\right)\right)$, the fintech can still capture the maximum borrower surplus, as these borrowers still choose the fintech and default, with an actual repayment of βa.

Therefore, finer information—in this extreme case, perfect information—does not increase fintech payoff due to competition and debt contract. This interesting result also suggests the existence of another equilibrium in this setting, where the perfectly informed fintech only uses a cut-off and no additional information. In this equilibrium, the fintech lends exclusively to borrowers with $a \geq \underline{a}^f(0)$ and randomly sets interest rates over $\left[\underline{r}^b, R^b\right)$, with some loans being risky. This equilibrium exactly corresponds to the special case of $c \to 0$ in Theorem 1.

As additional information beyond the threshold does not provide any benefit, when it comes at a cost as in Theorem 1, the structure of single-threshold information strictly dominates finer structures. Therefore, the single-threshold information structure arises as the unique equilibrium.

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, any lender has 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). 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 (see 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 a lot of data, such as in-house transaction histories, offer the same interest rate to customers, even when they have significantly different observable characteristics.

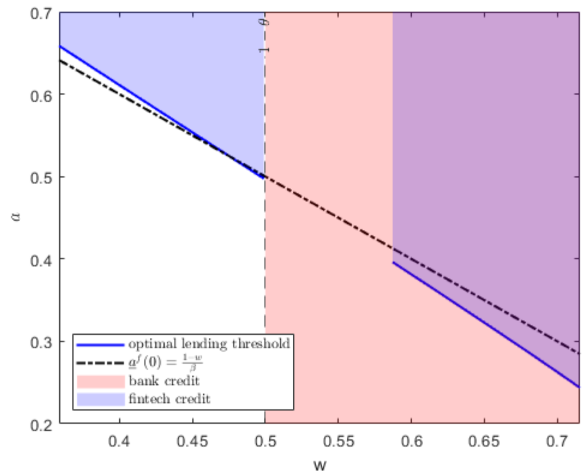
My theory offers some fresh insight in understanding the "coarseness" of the lending practice. Even if information is free, unsecured lending does not customize its offers based on information, because competition from the secured lending option eliminates information rent. Furthermore, my model suggests that tailored pricing only arises in less competitive environments. Therefore, a testable implication is that unsecured lending should be coarse at the loan origination stage, when competing offers are more common. However, once the loan is taken, the lender gains a monopolistic power, and we should observe sophisticated and customer-tailored fee setting.

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. In this subsection I discuss the resulting landscape of lending and the implications of 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

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).

and a the latent credit quality. In this part, based on the previous competition equilibrium results, I summarize the areas where each of the two lending services prevails within this two-dimensional space.

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). The fintech, thanks to its front-end business model, relies on a new repayment enforcement technology suitable for borrowers with high latent qualities, and importantly, it acquires information to screen out ineligible borrowers to mitigate adverse selection. 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 low LTV (high w) 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.

The paper thus highlights further specialization in customers based on the latent quality. In contrast, under canonical common-value setting, screening is correlated across lenders to select high quality borrowers that everyone cares about.

Lenders compete for borrowers who have both credit access. In wealthy markets where customer surplus is high, there is room for the fintech to compete for customers who were previously squeezed by the bank. In markets with mid-ranged w, however, even the bank has tight margin. Hence, it becomes challenging for the fintech to compete in the presence of information costs, leading the fintech to scale back and exit these markets.[22] 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) where the fintech lender (Upstart) generates profits from both unbanked low-FICO customers and from high-FICO customers. Additionally, in line with further specialization in latent quality a, the fintech picks up the "invisible primes" from low-FICO borrowers, who correspond to borrowers with $a \geq \hat{a}$ despite $w < 1 - \theta$ in my model; among high-FICO borrowers, some are only selected by the bank model rather than the fintech model.

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 are different from 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 the new technology is about acquiring information at a lower cost. As the quality of information determines lender strength

[22] 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.

(due to the common value auction framework), the new lender becomes the strong lender and builds rent over time, at the cost of traditional lending which eventually makes zero profits. In contrast, my model highlights that the fintech's lending technology involves both "enforcement" and "information acquisition;" it matters which technology we are discussing 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.,*
$$\frac{\partial \hat{a}}{\partial c} > 0, \; \frac{\partial \pi^b\left(r^b; w\right)}{\partial c} < 0.$$

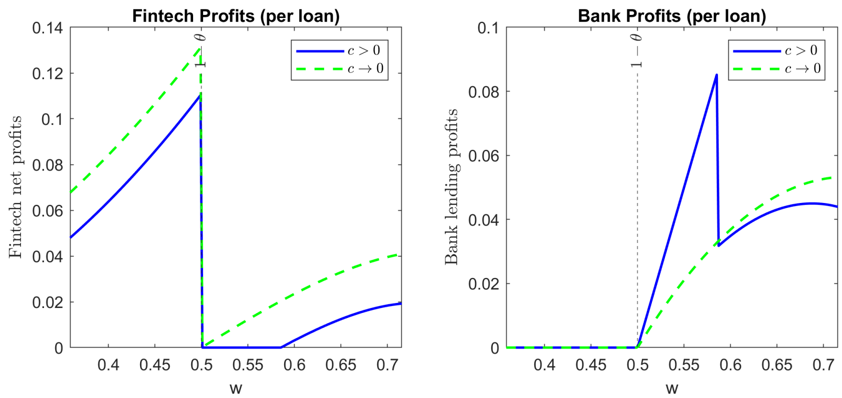
Proof. See Appendix 6.3. □

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, which hurts bank profit. 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.[23]

In sharp contrast, improvement in information technology (a smaller c) increases the competitor bank's profits. The right panel of Figure 6 illustrates this point. There, we observe that 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 $c \to 0$.

[23]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 $c > 0$ ($c \to 0$).

The intuition behind this intriguing result is that costly information acquisition leads to lax screening relative to the friction-less benchmark. In markets where the two lenders compete, the borrower population is relatively less risky with low LTV. Under Assumption 1, the medium borrower is positive NPV to the fintech, so the lemon problem is not that severe to begin with. As a result, the fintech's imperfect screening due to costly information only teases out the easily identified "extreme lemons," but still serves some ineligible borrowers. Now, suppose that the information becomes cheaper to acquire. The fintech is then able to identify and exclude some previously included lemons, leading it to compete for fewer customers and hence a more focused lending. This, in turn, benefits the traditional bank, whose lending is based on collateral anyway. 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 increase 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 canonical setting, the old fashioned lending 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 traditional banking to fight back, besides investing in information technology (IT equipment, software, algorithms) as predicted in canonical models (see He, Jiang, Xu, and Yin, 2022), it would need to build certain infrastructure that bundles the front-end services altogether. 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 to all borrowers there. Earlier discussion in Section 3 shows how fintech lending prospers as a new lending service via screening out ineligible borrowers, but this resolution requires low learning cost, which is likely to happen gradually with technology advancement and data accumulation. Nevertheless, this is a less efficient resolution because the fintech has to gather information independently in each market it would like to enter.

As this section's highlight, with the blessing of the big data technology, the fintech's expansion to wealthy markets can be an endogenous outcome of its early-stage lending in the unbanked population. By enabling cross-market predictability, big data technology allows fintech companies to extrapolate their learnings from existing markets and apply them to new markets of wealthy borrowers, significantly reducing the information cost. My model thus provides insights into the fintech expansion in the past decade.

4.1 No Information Benchmark and Implication on Expansion

In order to demonstrate why information technology is essential for fintech to compete, let us consider the benchmark case where information cost c is infinitely high, leaving the fintech uninformed. This benchmark reflects the early stage of the digital lending industry, when data is still not sufficient for effective information processing. For this discussion, I will omit the indexation of w, as the markets remain independent at this point.

Suppose $w \geq 1-\theta$; would the fintech lender enter the market? Let us define $r^{f,be}$ as the fintech's break-even interest rate in the absence of adverse selection, where adverse selection occurs as low-quality borrowers choose to default with the fintech rather than secured lending with the bank. Essentially, $r^{f,be}$ is the *minimum* default premium needed by the fintech to cover the costs of a loan; recall that $R^f(a) \equiv \frac{\beta a}{1-w} - 1$ is the maximum interest rate payment from borrower (w, a) to the fintech, and then

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

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;*

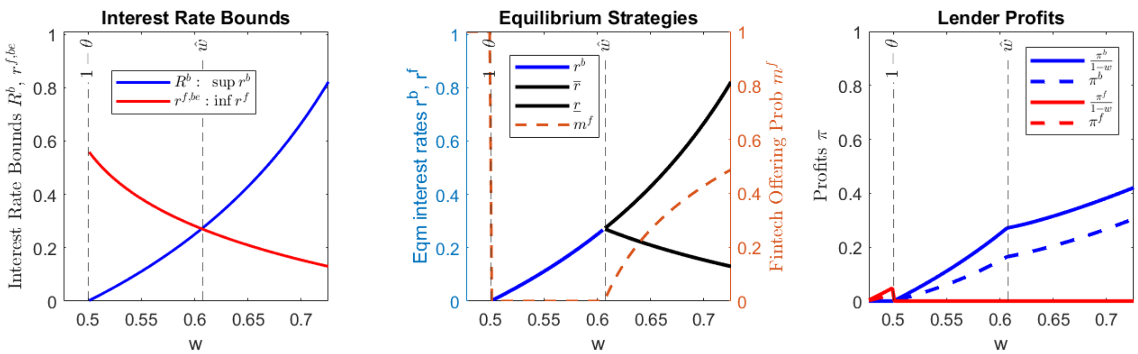
2. *when $w > \hat{w}$, the fintech randomly makes an offer.*

Proof. See Online Appendix 7.3 for proof and equilibrium characterization. □

During the early stages of fintech lending, when there is limited platform data available, the fintech only relies on the publicly available credit quality information—which is 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 these markets, when w is relatively low, borrowers are riskier but the competing bank is more aggressive due to its own tight margins. In the left panel of Figure 7, we can see that the required default premium $r^{f,be}$ is even higher than the maximum bank rate R^b for

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.

$1-\theta \leq w \leq \hat{w}$. Under such circumstances, lending would only incur losses for the fintech, therefore it would choose to exit these markets instead.

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 instead of a Bertrand outcome. 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 exits.

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. Even without information acquisition, the fintech occasionally makes loans in these markets and serves some borrowers (Proposition 3). However, it only makes profits beyond underserved markets when it actively acquires information to effectively screen out ineligible borrowers, as shown in Section 3. As more data is accumulated, the information cost decreases over time, until eventually the fintech has an incentive to acquire information to screen out ineligible borrowers. This new fintech lending service exists alongside traditional collateralized lending, but serves borrowers of high latent qualities with different enforcement thanks to its unique front-end infrastructure.

However, this resolution is costly as 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 fintech companies predominantly serve the unbanked population, as Proposition 3 highlights. A lot of data accumulated during the early stages in these unbanked market may not be useful for expanding into wealthy borrowers, and the fintech may have to start from scratch in these markets.

The advent of big data technology has significantly reduced information costs by enabling out-of-sample predictability, making early-stage data accumulation useful for expanding into other markets. Fintech companies, with their unique lending service and digital front-end, can leverage big data technology to identify latent traits that are correlated between even observably heterogeneous groups, such as unbanked and wealthy customers. Therefore, the fintech industry can use the information collected from its early-stage operations in unbanked markets to develop predictive models for identifying potential customers in wealthy markets, reducing the cost and time required for establishing effective screening. 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 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—with the aid of the above mentioned technology progresses—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. When the fintech has acquired an information structure $\mathcal{P}^w$ in some market w, it means that the fintech has established an algorithmic model that could be used to assess another market $w' \neq w$ and identify the same categorical traits in $\mathcal{P}^w$.

Formally, recall I have assumed that the information cost of establishing an algorithm for the first time is $c \cdot I(\mathcal{P}^w)\,dw$. When applying an established algorithm to another market $w' \neq w$, i.e., $\mathcal{P}^{w'} = \mathcal{P}^w$, the information cost is reduced to $\delta c \cdot I(\mathcal{P}^w)\,dw$ with $\delta \in (0,1)$. This means that the fintech pays a cost in collecting the data of new customers, but the algorithm systematically categorizes customers into $\mathcal{P}^w$ with much less cost than in the first market w.[24] If the fintech decides to acquire *new information* $\mathcal{P}^{w'} \neq \mathcal{P}^w$ instead of applying the established algorithm, then the unit information cost is still c. To summarize, we model the fintech's superior cross-market forecasting via the following information cost:

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

Note that setting $\delta = 1$ nests Section 3 within the current model.

4.3 Fintech Expansion

The big data technology enables cross-market forecasting, resulting in markets that are no longer independent. As a consequence, solving for the credit market equilibrium becomes highly complex. However, I argue that information acquisition is path-independent, and thus the equilibrium could be solved via a static problem. In a general dynamic problem, the fintech makes information acquisition and lending decisions step by step. When creating a new algorithm, the fintech takes into account its future predictability on other markets, resulting in path-independence of the benefit of information acquisition. Moreover, the

[24] Because markets w are continuous and each is zero measure, this information cost is also technically convenient so that the total cost does not become negligible.

cost of information acquisition, under an entropy setting, is also path-independent. To be more specific, in this static game, the fintech jointly chooses an information structure profile $\{\mathcal{P}^w\}_{w\in[0,\overline{w}]}$ for all markets to maximize the total net profits, with the cross-market information spillovers in Eq. (25).

My analysis of this challenging problem will focus on the theme of competition between different lending services, while leaving the full-blown characterization of the fintech's expansion across markets 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 its lending services to new markets.

Proposition 4. *The equilibrium information structure profile $\{\mathcal{P}^{*w}\}$ is a decreasing step function $\hat{a}(w)$ that is defined over the markets where the fintech acquires information.*

Specifically, there exists some finite n and a sequence of cutoffs $\hat{a}_1(w_1), \hat{a}_2(w_2), \cdots, \hat{a}_n(w_n)$ with $\hat{a}_1 > \hat{a}_2 > \cdots > \hat{a}_n$ and $w_1 < w_2 < \cdots < w_n$, so that

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

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

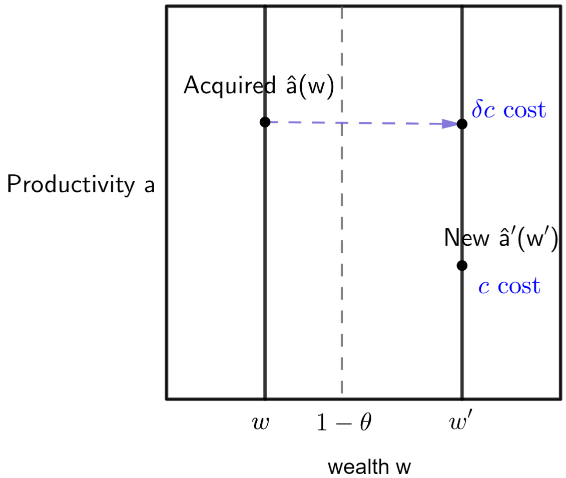
   and the fintech rejects borrowers of $a < \hat{a}_i$;

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 7.4. □

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. Acquiring new information only slightly improves screening due to the continuity of the markets, while the costs of doing so are much higher than those of applying established algorithms. Second, 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

Figure 8: Big Data Technology: Cross-Market Forecasting

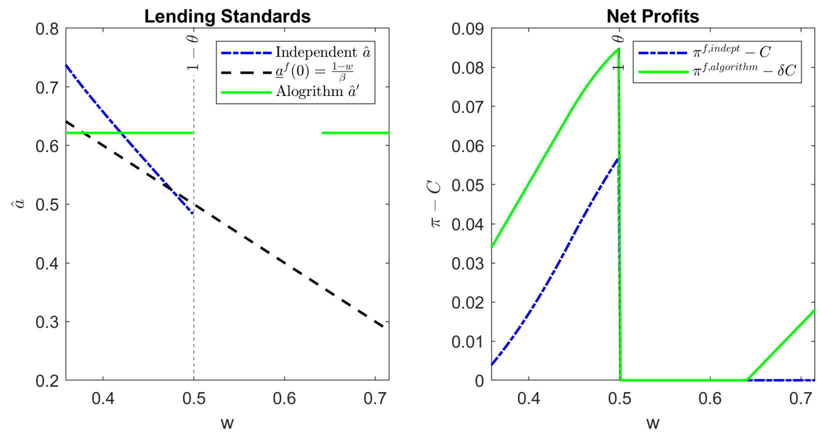


lending, and the purpose of information is to screen out risky loans. This point echoes the main take-away from Theorem 1. Last, as w increases, there are fewer lemons, and the fintech has an incentive to lower the screening standard, resulting in decreasing $\hat{a}(w)$. Taken together, the equilibrium expansion policy is to only lower $\hat{a}$ at critical markets $\{w_i\}$ to improve screening.

Proposition 4 thus reduces the problem of information acquisition 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. In the figure, suppose that in market w, a relatively high screening standard $\hat{a}(w)$ is used. When serving less risky customers in another market $w' > w$, the fintech can choose between applying the same algorithm $\hat{a}(w)$, which has a smaller unit information cost δc but maintains a high screening standard, or 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, which gives a lower bound of

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.

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

Furthermore, with the big data technology, the fintech can position itself as a more specialized and less aggressive competitor to the traditional banking sector, as its strategies are influenced by algorithmic models developed from unbanked markets. In these markets, a high lending standard is preferable in order to pick up the "invisible primes." When the fintech leverages the inter-market information spillovers, screening in other markets may be tilted towards this cherry-picking standard. As a result, the fintech competes for fewer customers, which can lead to higher profits for both lenders. On the other hand, when fintech acquires information independently for each market, competition is fiercer as the customized lending standard would be relatively lower where the bank is present.

This "invisible prime" strategy of fintech lending is empirically supported in Di Maggio, Ratnadiwakara, and Carmichael (2021), where the fintech lender applies algorithm models for lending decisions. The model picks up "invisible prime" in markets of low FICO score borrowers and is still more selective than the traditional bank's model in markets of high FICO score borrowers, suggesting out-of-sample predictability.

In practice, 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. Additionally, the static problem we just discussed may not accurately capture the market in the presence of realistic frictions such as capital layout or discounting. To address these concerns, an example in Online Appendix 7.4 considers the expansion of a fintech lender with a "history." The fintech lender currently operates in poor markets with a high lending standard and is considering expanding into new markets with a wealthier population. I leave the full-blown analysis of such dynamics for future research.

5 Conclusion

Fintech lending has disrupted traditional banking with fast, flexible services combined innovative screening powered by big data technology, 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 big tech companies like Amazon and Walmart into lending. Another disruptive force is the rise of new payment companies like Square and Stripe that emerged in response to the historically slow and expensive U.S. payment system. With their abundance of customer data and front-end enforcement capabilities, they have the potential to disrupt traditional lending.

My research highlights the unique services provided by fintech lenders and the differentiated competition. Especially for retail lending, information is only valuable when combined with effective enforcement, and 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, as nonbank lenders, fintechs share the same funding side limitations, which restrict their ability to offer, say credit lines or large-sized loans that are areas where depository institutions 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).

References

Acemoglu, Daron, Ali Makhdoumi, Azarakhsh Malekian, and Asuman Ozdaglar, 2019, Too much data: Prices and inefficiencies in data markets, Discussion paper National Bureau of Economic Research.

Agarwal, Sumit, Shashwat Alok, Pulak Ghosh, and Sudip Gupta, 2020, Financial inclusion and alternate credit scoring for the millennials: Role of big data and machine learning in fintech, Discussion paper Working Paper.

Allen, Franklin, Xian Gu, and Julapa Jagtiani, 2020, A survey of fintech research and policy discussion, .

Babina, Tania, Greg Buchak, and Will Gornall, 2022, Customer data access and fintech entry: Early evidence from open banking, *Available at SSRN*.

Balyuk, Tetyana, Allen N Berger, and John Hackney, 2020, What is fueling fintech lending? the role of banking market structure, *The Role of Banking Market Structure (June 23, 2020)*.

Banerjee, Priyodorshi, 2005, Common value auctions with asymmetric bidder information, *Economics Letters* 88, 47–53.

Bao, Zhengyang, and Difang Huang, 2021, Shadow banking in a crisis: Evidence from fintech during covid-19, *Journal of Financial and Quantitative Analysis* pp. 1–57.

Beaumont, Paul, Huan Tang, and Eric Vansteenberghe, 2022, The role of fintech in small business lending, *Available at SSRN 4260842*.

Ben-David, Itzhak, Mark J Johnson, and René M Stulz, 2021, Why did small business fintech lending dry up during march 2020?, Discussion paper National Bureau of Economic Research.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri, 2020, On the rise of fintechs: Credit scoring using digital footprints, *The Review of Financial Studies* 33, 2845–2897.

Berg, Tobias, Andreas Fuster, and Manju Puri, 2021, Fintech lending, Discussion paper National Bureau of Economic Research.

Berger, Allen N, and Gregory F Udell, 1995, Relationship lending and lines of credit in small firm finance, *Journal of business* pp. 351–381.

Besanko, David, and Anjan V Thakor, 1987, Collateral and rationing: sorting equilibria in monopolistic and competitive credit markets, *International economic review* pp. 671–689.

Biancini, Sara, and Marianne Verdier, 2019, Bank-platform competition in the credit market, *Available at SSRN 3446694*.

Boot, Arnoud WA, and Anjan V Thakor, 1994, Moral hazard and secured lending in an infinitely repeated credit market game, *International economic review* pp. 899–920.

Broecker, Thorsten, 1990, Credit-worthiness tests and interbank competition, *Econometrica: Journal of the Econometric Society* pp. 429–452.

Bryzgalova, Svetlana, Markus Pelger, and Jason Zhu, 2021, Forest through the trees: Building cross-sections of stock returns, *Available at SSRN 3493458*.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Chu, Yinxiao, and Jianxing Wei, 2021, Fintech entry and credit market competition, *Available at SSRN 3827598*.

Cumming, Douglas J, Andrea Martinez Salgueiro, Robert Reardon, and Ahmed Sewaid, 2020, Covid-19 bust, policy response, and rebound: Equity crowdfunding and p2p vs. banks, *Journal of Technology Transfer (Forthcoming)*.

De Roure, Calebe, Loriana Pelizzon, and Anjan Thakor, 2022, P2p lenders versus banks: Cream skimming or bottom fishing?, *The Review of Corporate Finance Studies* 11, 213–262.

Dell'Ariccia, Giovanni, and Robert Marquez, 2004, Information and bank credit allocation, *Journal of Financial Economics* 72, 185–214.

——— , 2006, Lending booms and lending standards, *The Journal of Finance* 61, 2511–2546.

Di Maggio, Marco, Dimuthu Ratnadiwakara, and Don Carmichael, 2021, Invisible primes: Fintech lending with alternative data, *Available at SSRN 3937438*.

Di Maggio, Marco, Emily Williams, and Justin Katz, 2022, Buy now, pay later credit: User characteristics and effects on spending patterns, Discussion paper National Bureau of Economic Research.

Di Maggio, Marco, and Vincent Yao, 2020, Fintech borrowers: Lax-screening or cream-skimming?, *Available at SSRN 3224957*.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, 2019, The role of technology in mortgage lending, *The Review of Financial Studies* 32, 1854–1899.

Gambacorta, Leonardo, Yiping Huang, Zhenhua Li, Han Qiu, and Shu Chen, 2020, Data vs collateral, .

Ghosh, Pulak, Boris Vallee, and Yao Zeng, 2021, Fintech lending and cashless payments, *Available at SSRN 3766250*.

Goldstein, Itay, Chong Huang, and Liyan Yang, 2022, Open banking under maturity transformation, *Available at SSRN*.

Gopal, Manasa, and Philipp Schnabl, 2020, The rise of finance companies and fintech lenders in small business lending, *NYU Stern School of Business*.

Gorton, Gary, and Andrew Winton, 2003, Financial intermediation, in *Handbook of the Economics of Finance*, vol. 1 . pp. 431–552 (Elsevier).

Hart, Oliver, 1995, *Firms, contracts, and financial structure* (Clarendon press).

——— , and John Moore, 1994, A theory of debt based on the inalienability of human capital, *The Quarterly Journal of Economics* 109, 841–879.

Hau, Harald, Yi Huang, Hongzhe Shan, and Zixia Sheng, 2019, How fintech enters china's credit market, in *AEA Papers and Proceedings* , vol. 109 pp. 60–64.

Hausch, Donald B, 1987, An asymmetric common-value auction model, *The RAND Journal of Economics* pp. 611–621.

Hauswald, Robert, and Robert Marquez, 2003, Information technology and financial services competition, *The Review of Financial Studies* 16, 921–948.

He, Zhiguo, Jing Huang, and Jidong Zhou, 2023, Open banking: Credit market competition when borrowers own the data, *Journal of Financial Economics* 147, 449–474.

He, Zhiguo, Sheila Jiang, Douglas Xu, and Xiao Yin, 2022, Investing in bank lending technology: It spending in banking, Discussion paper National Bureau of Economic Research.

He, Zhigu, and Arvind Krishnamurthy, 2012, A model of capital and crises, *The Review of Economic Studies* 79, 735–777.

Holmstrom, Bengt, and Jean Tirole, 1997, Financial intermediation, loanable funds, and the real sector, *the Quarterly Journal of economics* 112, 663–691.

Hu, Yunzhi, and Pavel Zryumov, 2022, Lending competition and funding collaboration, *Available at SSRN 4298701*.

Jansen, Mark, Hieu Nguyen, and Amin Shams, 2021, Rise of the machines: The impact of automated underwriting, *Fisher College of Business Working Paper* p. 019.

Jiang, Erica Xuewei, 2019, Financing competitors: shadow banks' funding and mortgage market competition, *USC Marshall School of Business Research Paper Sponsored by iORB, No. Forthcoming*.

Kagel, John H, and Dan Levin, 1999, Common value auctions with insider information, *Econometrica* 67, 1219–1238.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein, 2002, Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *The Journal of finance* 57, 33–73.

Kehoe, Timothy J, and David K Levine, 1993, Debt-constrained asset markets, *The Review of Economic Studies* 60, 865–888.

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit cycles, *Journal of political economy* 105, 211–248.

Lian, Chen, and Yueran Ma, 2021, Anatomy of corporate borrowing constraints, *The Quarterly Journal of Economics* 136, 229–291.

Liu, Lei, Guangli Lu, and Wei Xiong, 2022, The big tech lending model, Discussion paper National Bureau of Economic Research.

Marquez, Robert, 2002, Competition, adverse selection, and information dispersion in the banking industry, *The Review of Financial Studies* 15, 901–926.

Milgrom, Paul, and Robert J Weber, 1982, The value of information in a sealed-bid auction, *Journal of Mathematical Economics* 10, 105–114.

Myerson, Roger B, 1981, Optimal auction design, *Mathematics of operations research* 6, 58–73.

Ouyang, Shumiao, 2021, Cashless payment and financial inclusion, *Available at SSRN 3948925*.

Parlour, Christine A, Uday Rajan, and Haoxiang Zhu, 2021, When fintech competes for payment flows, *Available at SSRN*.

Petersen, Mitchell A, and Raghuram G Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *The journal of finance* 49, 3–37.

Rajan, Raghuram G, 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *The Journal of finance* 47, 1367–1400.

Rampini, Adriano A, and S Viswanathan, 2010, Collateral, risk management, and the distribution of debt capacity, *The Journal of Finance* 65, 2293–2322.

Riordan, Michael, 1993, Competition and bank performance: A theoretical perspective, in Colin Mayer, and Xavier Vives, ed.: *Capital Markets and Financial Intermediation* . chap. 10, pp. 328–43 (Cambridge University Press: Cambridge, New York and Melbourne).

Sengupta, Rajdeep, 2007, Foreign entry and bank competition, *Journal of Financial Economics* 84, 502–528.

Sharpe, Steven A, 1990, Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships, *The Journal of Finance* 45, 1069–1087.

Stiglitz, Joseph E, and Andrew Weiss, 1981, Credit rationing in markets with imperfect information, *The American economic review* 71, 393–410.

Tang, Huan, 2019, Peer-to-peer lenders versus banks: substitutes or complements?, *The Review of Financial Studies* 32, 1900–1938.

Thakor, Anjan V, 1996, Capital requirements, monetary policy, and aggregate bank lending: theory and empirical evidence, *The Journal of Finance* 51, 279–324.

Vallee, Boris, and Yao Zeng, 2019, Marketplace lending: A new banking paradigm?, *The Review of Financial Studies* 32, 1939–1982.

Varian, Hal R, 1980, A model of sales, *American Economic Review* 70, 651–659.

Vives, Xavier, 2019, Digital disruption in banking, *Annual Review of Financial Economics* 11, 243–272.

——— , and Zhiqiang Ye, 2021, Information technology and bank competition, *Available at SSRN 3863988*.

6 Technical Appendix

6.1 Proof of Theorem 1

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

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

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 $\mathcal{P}$,

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

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

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

Then we can derive the expression for $I(\mathcal{P})$ as follows:

$$I(\mathcal{P}) = -\int_A g(a) \log g(a)\, da + \sum_{A^i \in \mathcal{P}} \mathbb{P}\left(A^i\right) \left[\int \mathbf{1}_{a \in A^i} \frac{g(a)}{\mathbb{P}(A^i)} \log \frac{g(a)}{\mathbb{P}(A^i)} da\right]$$

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

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

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

□

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 $\mathcal{P} = \{[\underline{a}, \hat{a}), [\hat{a}, \overline{a}]\}$, where $\hat{a}$ satisfies*

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

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

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

Then we can construct a new partition

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

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 $\left\{A^{rej}, A^{offer}\right\}$:

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

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

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

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:

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

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 $r^f = r^b - \epsilon$ or reject the borrower for any event $A \in \mathcal{P}$.

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 $r^f = r^b - \epsilon$ 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 $\hat{A} \in \mathcal{P}$, so that around r*

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

Proof. Note that if for any $A', A'' \in \mathcal{P}$, 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 $\hat{r} \in R' \cap R''$ 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,

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

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

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

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

where "$\min\{\cdot, 1\}$" in Eq. (27) serves to cap the CDF $\tilde{F}^f \left(r | A' \right)$ below 1 when adding its mass; when binding, the "$+\mathbf{1}_{r \in (R' \cap R'')} \cdot \left[F^f \left(r | A'' \right) - \tilde{F}^f \left(r | A' \right) \right]$" 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, $F^f(r) \equiv \sum_{A^i} \mathbb{P}(A_i) F^f(r | A_i)$ remains unchanged.

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

$$\tilde{R}' \equiv R' \cup \left(R' \cap R'' \right), \; \tilde{R}'' \equiv R'' \setminus \left(R' \cap R'' \right),$$

under which the lemma holds. If $\tilde{F}^f \left(r | A' \right) = 1$, then around any $\hat{r} \in R' \cap R''$, 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, $F^f(\hat{r}) = \mathbb{P}(A') \tilde{F}^f(\hat{r} | A') + \mathbb{P}(A'') \tilde{F}^f(\hat{r} | A'') = \mathbb{P}(A') + \mathbb{P}(A'') \tilde{F}^f(\hat{r} | A'')$ 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',

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

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

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 $\max_{r\in B(\hat{r})}[1-F^j(r)]r$. Then at least one of them would have a deviation incentive. In my model, the profits are

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

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

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.[25] 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, $(\hat{r}, \hat{r}+\epsilon)$ is not a subset of the other lender j''s support. Suppose not; then on any borrowers that lender j' would charge $\hat{r}+\epsilon$ potentially, it would strictly prefer charging $\hat{r}-\epsilon$. It follows that one profitable deviation for lender j is to increase the quote at mass point to $r^j \in (\hat{r}, \hat{r}+\epsilon)$. 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 $\overline{r}^f \leq \overline{r}^b$. This is because when $r^f > \overline{r}^b$, the fintech's profit is

[25] 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.

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 $r^b \in \left[\overline{r}^f, \overline{r}^b\right]$ at R^b. Then the fintech has a profitable deviation by marginally increasing the interest rate $\overline{r}^f - \epsilon$ to $\overline{r}^f + \epsilon$ (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 $r^j \in \left(\underline{r}^j, \underline{r}^{j'}\right)$ at $\underline{r}^{j'} - \epsilon$.

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 $r' + \epsilon$ (as the demand does not change). Suppose the fintech has gap in (r', r''). According to Eq. (30), the bank's profit when charging $r^b \in [r', r'']$ 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 $w \geq 1 - \theta$, first, I solve for for the bank strategy from the fintech's indifference condition.

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

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

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

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 $\pi^f(r_n, A^i) = \pi^f(r, A^i)$, we have

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

which leads to

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

The equality holds for any $r \in R^i$ and any sequence $\{r_n\} \subset R^i$ 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

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

In addition, Eq. (32) holds over the entire common support $\left[\underline{r}, R^b\right]$. According to Lemma 4, for any bank quote $r \in \left[\underline{r}, R^b\right]$, we can find an event $\hat{A} \in \mathcal{P}$ 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

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

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 $A^i \in \mathcal{P}$. If a borrower defaults and repays $R^f(a) \equiv \frac{\beta a}{1-w} - 1$, as long as $R^f(a) \in \left[\underline{r}, R^b\right]$, 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 $A^i \in \mathcal{P}$ with $m^f(A^i) > 0$, the fintech profit when quoting any $r \in \left[\underline{r}, R^b\right]$ is

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

$$+ K \int_{\underline{a}^f(r)}^{\overline{a}} \mathbf{1}_{A^i} dG(a)$$

$$= \int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{A^i} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{A^i} dG(a),$$

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 $\mathcal{P}$ 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 $\mathbf{a^{rej}}, \mathbf{a^{offer}}$ of equal measure such that

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

Then the fintech has a profitable deviation to the following partition

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

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

$$\underbrace{\int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{\boldsymbol{a}^{rej}} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{\boldsymbol{a}^{rej}} dG(a)}_{\mathbf{a^{rej}} \in \hat{A}^{offer},\ \text{offer } r \in [\underline{r}, R^b)} + \underbrace{\int_{\mathbf{a^{offer}}} 0 \cdot g(a)\, da}_{\mathbf{a^{offer}} \in \hat{A}^{rej}, \text{reject}}$$

$$> \underbrace{\int_{\boldsymbol{a}^{rej}} 0 \cdot g(a)\, da}_{\boldsymbol{a}^{rej} \in A^{rej}, \text{reject}} + \underbrace{\int_{\underline{a}}^{\underline{a}^f(\underline{r})} \mathbf{1}_{\mathbf{a_2^{offer}}} \cdot R^f(a)\, dG(a) + K \int_{\underline{a}^f(\underline{r})}^{\overline{a}} \mathbf{1}_{\mathbf{a_2^{offer}}} dG(a)}_{\mathbf{a^{offer}} \in A^{offer},\ \text{offer } r \in [\underline{r}, R^b)},$$

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

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

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

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

where lending profits are given by

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

and the entropy of a single-threshold partition is

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

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

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

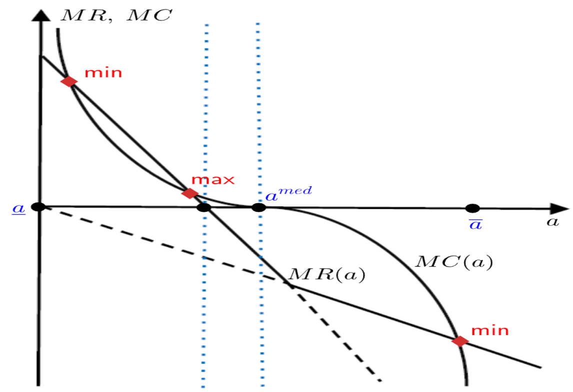
where $\underline{a}^f(r) \equiv \frac{(1-w)(1+r)}{\beta}$ is the lowest type who does not default on quote r. If $\hat{a} \geq \underline{a}^f(\underline{r})$, the marginal type $\hat{a}$ does not default on the lower-bound interest rate $\underline{r}$. In this case, we solve for $\underline{r}$ from 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 $R^f(a) \geq 0$ and $\log \frac{G(a)}{1-G(a)} < 0$, so

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

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 $\hat{a}$)

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

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

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

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 $a \geq \hat{a} = \overline{a} - \epsilon$ (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 $w \geq 1-\theta$,

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

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

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

We know that

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

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 $Q(\hat{a}) \triangleq -(1-w) h(w) R^f(a) - c \log \frac{G(\hat{a})}{1-G(\hat{a})} = 0$ 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

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

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

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 $\hat{a}, \underline{r}, F^{j}(r)$ in response to β and c. We have the FOC

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

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

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

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

From the implicit function theorem, we have

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

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

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 $F^b\left(r\right)=1-\frac{\underline{r}}{r}$, a higher (lower) equilibrium $\underline{r}$ make the bank's strategy less aggressive in the sense of first order stochastic dominance; i.e., for $\underline{r}'>\underline{r}$, $F^b\left(r;\underline{r}'\right)\succ^{FOSD} F^b\left(r;\underline{r}\right)$. From $F^f\left(r\right)=1-\frac{R^b-r}{1-G\left(\underline{a}^f(r)\right)}\cdot G\left(\hat{a}\right)$, 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

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

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 $Y^f\left(\hat{a}\right)$ denote the fintech's net profits (net of information cost),

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

$$= (1-w)\, dH(w) \cdot \left\{ \int_{\hat{a}}^{\underline{a}^f(\underline{r})} R^f(a)\, dG(a) + \left[1 - G\left(\underline{a}^f(\underline{r})\right)\right] \underline{r} \right\} - cI(\mathcal{P}(\hat{a})).$$

By the envelope theorem, we have

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

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

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.

□

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 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 offers the highest rate $R^f(a)$;*

2. *When $w \geq 1-\theta$, the bank makes an offer with randomized interest rate $r^b \in \left[\underline{r}^b, R^b\right]$ according to CDF*
$$F^b(r; w) = 1 - \frac{\underline{r}^b}{r}, \tag{39}$$
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
$$\begin{cases} m^f(a) = 0, & \text{if } a < \underline{a}^f(0), \\ m^f(a) = 1,\ r^f(a) = R^f(a), & \text{if } \underline{a}^f(0) \leq a < \underline{a}^f\left(\underline{r}^b\right), \\ m^f(a) = 1,\ r^f(a) < R^f(a), & \text{if } a \geq \underline{a}^f\left(\underline{r}^b\right), \end{cases}$$
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,
$$\pi^b \propto R^b \cdot G\left(\underline{a}^f(0)\right);$$
The fintech's profit from each borrower type a is
$$\pi^f\left(r^f \middle| a; w\right) \propto \begin{cases} 0, & \text{if } a < \underline{a}^f(0), \\ R^f(a), & \text{if } \underline{a}^f(0) \leq a < \underline{a}^f\left(\underline{r}^b\right), \\ \underline{r}^b, & \text{if } a \geq \underline{a}^f\left(\underline{r}^b\right). \end{cases}$$

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

For borrowers with $\underline{a} \leq a < \underline{a}^f(0)$, 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 $r^f = r^b - \epsilon$ for all borrowers with $a \geq \underline{a}^f\left(r^b - \epsilon\right)$ 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,

$$\pi^f\left(r^f\right) \propto \underbrace{\int^{\underline{a}(r^f)}}_{\text{low } a} \underbrace{\left[1 - F^b\left(R^f(a)\right)\right]}_{\text{winning prob}} \cdot \underbrace{R^f(a)}_{\text{repayment}} dG(a) + \underbrace{\int_{\underline{a}(r^f)} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^b\left(r^f\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^f}_{\text{repayment}}, \quad (40)$$

$$\pi^b\left(r^b\right) \propto G\left(\underline{a}^f(0)\right) \cdot r^b + \underbrace{\int_{\underline{a}(r^b)} dG(a)}_{\text{high } a} \cdot \underbrace{\left[1 - F^f\left(r^b\right)\right]}_{\text{winning prob}} \cdot \underbrace{r^b}_{\text{repayment}}, \quad (41)$$

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. (40) and (41), 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, $(\hat{r}, \hat{r} + \epsilon)$ is not a subset of the other lender j''s support: Suppose not; then on any borrowers that lender j' would charge $\hat{r} + \epsilon$ potentially, it would strictly prefer charging $\hat{r} - \epsilon$. It follows that one profitable deviation for lender j is to increase the quote at mass point to $r^j \in (\hat{r}, \hat{r} + \epsilon)$.[26] 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 $\overline{r}^b = \overline{r}^f \equiv \overline{r}$, and lower support $\underline{r}^f = 0 < \underline{r}^b$. It is wlog to focus on $\overline{r}^f \leq \overline{r}^b$. This is because when $r^f > \overline{r}^b$, the fintech's profit is a constant $\int^{\underline{a}(\overline{r}^b)} \left[1 - F^b\left(R^f(a)\right)\right] R^f(a)\, dG(a)$ (the first term in Eq. 40) 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 $r^b \in \left[\overline{r}^f, \overline{r}^b\right]$ at R^b. Then the fintech has a profitable deviation by marginally increasing the interest rate $\overline{r}^f - \epsilon$ to $\overline{r}^f + \epsilon$ (on the corresponding borrowers). As for lower supports, we have $\underline{r}^b > 0$ as bank profit is positive; within riskless loans, we have

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

$\underline{r}^f = 0$ 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 $r' + \epsilon$ (as the demand does not change). Suppose the fintech has gap in (r', r''). According to Eq. (41), the bank's profit when charging $r^b \in [r', r'']$ 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 7.2 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.,

$$r^f(a) = \arg\max \left(1 - F^b\left(r^f(a)\right)\right) r^f(a) \qquad (42)$$
$$s.t.\ r^f(a) \leq R^f(a).$$

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

$$F^b(r) = \begin{cases} 1 - \frac{\underline{r}^b}{r}, & \underline{r}^b \leq r < R^b, \\ 1, & r = R^b. \end{cases} \qquad (43)$$

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 $-f^b\left(r^f(a')\right) r^f + 1 - F^b\left(r^f(a')\right) > 0$ and $F^b(r) \leq 1 - \frac{\underline{r}^b}{r}$.[27] 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 $\overline{r}$.

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

Fintech's strategy over $r^f \in \left[\underline{r}^b, R^b\right)$ 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 $\phi(r) \equiv \left[r^f(a)\right]^{-1}$ to denote the marginal borrower who is charged with $r^f = r$. Then bank profit is

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

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

$$\frac{dr^f(a)}{da} = \frac{r(a)\,g(a)}{G\left(\underline{a}^f(0)\right) + 1 - G(a)}, \tag{44}$$

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 (44) indeed satisfies $r^f(a) \leq R^f(a)$, and generically the inequality is strict. This further pins down the banks strategy as Eq. (43).

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.

Bank profit is

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

Fintech profit is

$$\pi^f \propto \underbrace{\int_{\underline{a}^f(0)}^{\underline{a}^f(\underline{r}^b)} R^f(a)\,dG}_{\text{intermediate } a} + \underbrace{\int_{\underline{a}^f(\underline{r}^b)}^{\overline{a}} \left(1 - F^b\left(r^f(a)\right)\right) r^f(a)\,dG}_{\text{high } a\text{, compete with bank}}$$

$$\underbrace{=}_{F^b(r)=1-\frac{\underline{r}^b}{r}} \int_{\underline{a}^f(0)}^{\underline{a}^f(\underline{r}^b)} R^f(a)\,dG + \int_{\underline{a}^f(\underline{r}^b)} \frac{\underline{r}^b}{r^f(a)} r^f(a)\,dG$$

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

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

□

7.3 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 offer $r^f = R^f(\overline{a})$ iff $\mathbb{E}\left[R^f(\overline{a})\right] \geq 0$;*
2. *When $1 - \theta \leq w \leq \hat{w}$ where $r^{f,be}(\hat{w}) = R^b(\hat{w})$, only the bank makes an offer $r^b = R^b$;*
3. *When $w > \hat{w}$, the bank always makes an offer whereas the fintech randomly makes an offer with probability m^f; an offer'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 $r \in \left[r^{f,be}, R^b\right)$. When evaluated at $r = r^{f,be}$, we have $\pi^f\left(r^{f,be}\right) = 0$ and $\pi^b\left(r^{f,be}\right) \propto r^{f,be} > 0$; so the fintech randomly makes an offer with probability m^f and the bank always makes an offer.

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

$$\pi^b(r) \propto \underbrace{(1 - m_f)}_{\text{no fintech offer}} r + \underbrace{m_f}_{\text{fintech offer}} \underbrace{\left[1 - F^f(r)\right]}_{Pr.\ r^f > r^b} \cdot \underbrace{\left[1 - G\left(\underline{a}^f(r)\right)\right]}_{Pr.\ R^f(a) > r^b} r. \tag{45}$$

The fintech's profit is

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

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

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

□

7.4 Appendix for Section 4.3

Lemma 7. *Equilibrium information structure profile $\{\mathcal{P}^{*w}\}_{w \in [0, \overline{w}]}$ 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. $\square$

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

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

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

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

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. $\square$

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 $\hat{w} \in \left(\underline{w}, w_{(2)}\right)$ 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 $\hat{a}_h$.