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Fintech Lending and Credit Market Competition

Yinxiao Chu
University of International Business and Economics School of Banking and Finance
chuyinxiao@uibe.edu.cn

Jianxing Wei
University of International Business and Economics School of Banking and Finance
jianxing.wei@uibe.edu.cn (corresponding author)

Abstract

This article studies how the rise of financial technology (Fintech) lending affects credit access, interest rates, and social welfare. We consider a lending competition model with two incumbent banks and a Fintech lender, which use different information and technologies to assess borrower creditworthiness. We show that Fintech lending could negatively affect high-quality borrowers' access to credit when the Fintech lender's screening accuracy is superior to that of the banks. Furthermore, Fintech lending may worsen the allocative efficiency of credit and reduce social welfare under some conditions. Analytical and numerical results suggest that Fintech lending mostly reduces the expected interest rates.

I. Introduction

Credit markets worldwide are witnessing the rise of financial technology (Fintech) lending (e.g., Claessens, Frost, Turner, and Zhu (2018), Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2020)). In the U.S., the Fintech market share of new lending in the mortgage market reached approximately 14% in 2020 (Berg, Fuster, and Puri (2022)). In China, Bigtech firms, such as Ant Financial and Tencent, provide credit to millions of households and firms (Frost, Gambacorta, Huang, Shin, and Zbinden (2019), Hau, Huang, Shan, and Sheng (2019), (2021)). A recent survey conducted by McKinsey shows that the COVID-19 pandemic may have accelerated the growth of Fintech lending.[1]

A defining feature that differentiates Fintech lending from bank lending is the information and technology used to screen borrowers (Berg et al. (2022)). Banks have mainly relied on traditional credit scores and proprietary information accumulated during the lending relationship to screen borrowers (e.g., Agarwal and Hauswald (2010)). In contrast, Fintech lenders use big data analytics and nontraditional alternative data, such as phone and rent bills, shopping history, social media

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[1]"How U.S. customers' attitudes to Fintech are shifting during the pandemic," McKinsey, Dec. 17, 2020. The survey results are available at https://www.mckinsey.com/industries/financial-services/our-insights/how-us-customers-attitudes-to-fintech-are-shifting-during-the-pandemic.

activities, and Internet browsing history, to predict borrower creditworthiness. Researchers have analyzed the usefulness of alternative data in credit scoring and lending decisions.[2] In an influential study, Berg, Burg, Gombović, and Puri (2020) show that consumers' digital footprints (the information left online when people access or register on a web page) are valuable for predicting default and payment behaviors in an E-commerce platform. Moreover, Berg et al. (2020) find that the predictive power of a model that uses only the digital footprint variables equals or exceeds that of a model using traditional credit bureau scores. Their findings are further supported by a growing body of literature documenting the information content of alternative data in loan performance prediction (e.g., Frost et al. (2019), Gambacorta, Huang, Qiu, and Wang (2019), Agarwal, Alok, Ghosh, and Gupta (2020), Huang, Zhang, Li, Qiu, Sun, Wang, and Berger (2020), and Di Maggio and Yao (2021)).

Several commentators have suggested the potential benefits of using alternative data to expand credit to customers who lack credit history and are underserved by the traditional credit system. As pointed out by the Consumer Financial Protection Bureau director, Richard Cordray, "For these consumers, the use of unconventional sources of information may allow them to build a credit history and gain access to credit. By filling in more details of people's financial lives, this information may paint a fuller and more accurate picture of their creditworthiness. So adding alternative data into the mix may make it possible to open up more affordable credit for millions of additional consumers"[3]. Similar views on the beneficial role of Fintech lending in promoting financial inclusion are shared by many scholars (e.g., Jagtiani and Lemieux (2019), Agarwal et al. (2020), and Philippon (2020)).

Despite the positive view of Fintech lending in credit expansion, there is concern that the rise of Fintech lending poses a threat to incumbent financial institutions. Indeed, recent empirical studies have shown that Fintech lenders and banks compete on credit provision (e.g., Cornaggia, Wolfe, and Yoo (2019), Tang (2019), and Di Maggio and Yao (2021)). If Fintech lenders' ability to screen borrowers is sufficiently superior, they may be able to poach customers from incumbent lenders to extend their market share. In this case, the competition from Fintech lenders can create a threat of adverse selection for traditional banks, which has important implications for banks' strategic behaviors. For example, Cornaggia et al. (2019) empirically find that Fintech lenders poach the profitable borrowers of incumbent lenders and crowd out bank credit supply. Cornaggia et al. (2019) suggest that there may exist a tension between supporting the growth of new technology and maintaining access to existing brick-and-mortar financial services.

This article presents a stylized lending competition model to study the potential consequences of Fintech lending and alternative information for credit access, interest rates, and social welfare. We consider a credit market with two incumbent

[2]Earlier studies use publicly available data from marketplace lenders to analyze the information content of nontraditional data, such as friendship networks and nonstandard soft information, for screening purposes (e.g., Lin, Prabhala, and Viswanathan (2013), Iyer, Khwaja, Luttmer, and Shue (2016), and Jagtiani and Lemieux (2019)).

[3]The information can be found at https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-alternative-data-field-hearing/.

banks. Following Hauswald and Marquez (2006), a circular city is used to model the credit market, where banks and borrowers are located equidistantly on the perimeter of the circle. There are two types of borrowers in the credit market—the high-type (with high credit quality) and the low-type (with low credit quality). For a given borrower, its nearest bank has valuable proprietary information about its creditworthiness. For example, the proprietary information is the borrower's credit history or the loan officer's judgement. On the contrary, its farthest bank does not have such proprietary information. To capture the important role of geographical distance in bank lending, we also assume that the nearest bank's signal accuracy decreases with the lender–borrower distance. We call a borrower's nearest bank the inside bank and the farthest bank the outside bank.

There is one potential entrant lender, which has access to a Fintech technology that generates signals about the borrower's credit quality based on alternative information different from that used by banks. We refer to this entrant as the Fintech lender. If the Fintech lender enters, it will be placed at the center of the circle. To reflect that the traditional banks and Fintech lender use distinct information and technologies in lending decisions, we assume that for a given borrower, the private signals of its inside bank and the Fintech lender are conditionally independent. Moreover, the screening accuracy of the Fintech lender does not depend on geographical distance. Within this setup, the Fintech lender's signal accuracy can be either higher or lower than that of the inside bank depending on the borrower's specific location. This naturally captures the idea that, although banks have informational advantages in some market segments, Fintech lenders can compete with and even outperform banks in other segments.[4]

Section III provides a full characterization of the lending competition between two asymmetrically informed lenders with conditionally independent signals. We show that no pure-strategy equilibrium exists because of the "winner's curse"—winning a borrower indicates that other lenders are very likely to receive bad signals and reject the borrower. However, there exists a unique mixed-strategy equilibrium that crucially depends on the screening ability gap between the two lenders. When the screening ability gap is large, the less informed lender (i.e., the lender with a lower screening ability) sometimes rejects borrowers even upon seeing good signals, and earns zero expected profits in equilibrium. In contrast, the more informed lender (i.e., the lender with a higher screening ability) always makes an offer upon seeing a good signal and obtains a positive expected profit. However, when the screening ability gap is small, both lenders accept loan applications with good signals and obtain positive expected profits. In Section IV, we apply this result to characterize the equilibrium after the Fintech lender enters the market.

Section IV analyzes the implications of Fintech lending for credit market competition. We compare the equilibrium under two different credit markets: with and without Fintech lending. Before the Fintech lender's entry, each borrower can apply for loans from the inside and outside banks. Thus, the lending competition is

[4]As noted by Berg et al. (2022), empirical research indicates mixed results when comparing the realized delinquency rates of Fintech and bank loans for borrowers with similar observable characteristics.

between an informed bank and an uninformed one, similar to that in Hauswald and Marquez (2006). In equilibrium, the inside bank always offers credit to borrowers with good signals, while the outside bank rejects applications with a positive probability. The Fintech lender can directly compete with the two banks for borrowers upon entry. Thus, for a given borrower, the lending competition is between three asymmetrically informed lenders: a more informed, a less informed, and an uninformed lender. We show that in the three-lender competition game, it is never optimal for the outside bank to submit a bid. Hence, the equilibrium of the three-lender competition game is the same as that in the two-lender competition game between a borrower's inside bank and the Fintech lender. Therefore, we can apply the results derived in Section III to characterize the competition equilibrium with Fintech lending.

We show that there is an extensive vs. intensive trade-off regarding the effects of Fintech lending on borrowers' access to credit. On the one hand, Fintech lending provides borrowers with an alternative source of financing. Thus, a borrower is more likely to obtain credit as it has more chances to apply for credit and pass a lender's screening. This extensive increase effect is consistent with the credit expansion view of Fintech lending. On the other hand, Fintech lending discourages existing banks from bidding by creating a winner's curse problem—the borrowers' outside bank refrains from bidding, and the inside bank may decline to extend loans even after receiving a good signal if its screening accuracy is low compared to that of the Fintech lender. This is the intensive decrease effect of Fintech lending. The overall effects depend on the relative magnitude of these two countervailing forces, which in turn are determined by the type of borrowers and their distance to the inside bank. In particular, for high-type borrowers close to their inside bank, the extensive effect is dominant, and Fintech lending increases their credit access. However, for high-type borrowers far from their inside bank, the Fintech lender's screening ability is superior to that of the inside bank. Thus, Fintech lending exacerbates the winner's curse problem such that the existing banks' willingness to supply credit decreases substantially. In this case, the intensive decrease effect can outweigh the extensive increase effect. This result suggests that the popular view that Fintech lending improves credit access for borrowers with observably poor but actually good credit is not necessarily true.

Finally, we study the implications of Fintech lending for interest rates and social welfare. We show that Fintech lending unambiguously reduces the expected interest rates for borrowers close to their inside bank. Our numerical results suggest a similar interest rate reduction effect of Fintech lending for most borrowers far from their inside bank. From a social welfare perspective, it is efficient to finance more high-type borrowers and weed out low-type borrowers. We find that, in most cases, Fintech lending improves credit allocation efficiency and social welfare. However, there exist certain parameters such that Fintech lending reduces social welfare. This happens when the borrower's project returns and the Fintech lender's signal accuracy are low. In this case, the Fintech lender allows too many low-type borrowers to obtain loans, which offsets the benefit of financing more high-type borrowers and is thus detrimental to allocative efficiency.

Our article contributes to the growing literature on Fintech lending (see Berg et al. (2022) for a review) and its interaction with banking (e.g., Vives (2019), Thakor (2020)).[5] In theoretical work, Parlour, Rajan, and Zhu (2022) find that Fintech competition in payments may have adverse impacts on the credit market when consumers' payment data are useful for banks to assess borrowers' credit quality. He, Huang, and Zhou (2023) study the lending competition between a traditional bank and a Fintech lender with asymmetric screening abilities. They highlight the potential perverse effects of open banking initiatives (sharing banks' customer data with the Fintech lender) on borrowers when it widens the screening ability gap between the two lenders. However, none of these articles consider the potential impact of Fintech lending on credit access, a key question in evaluating the benefits and costs of Fintech lending. This article shows that once the strategic behaviors of incumbent banks are taken into account, Fintech lending does not necessarily benefit consumers in terms of access to credit.

This article is related to the literature on lending competition with asymmetric screening abilities (e.g., Sharpe (1990), Hauswald and Marquez (2003), (2006), von Thadden (2004), Banerjee (2005b), and He et al. (2023)).[6] In the context of repeated lending under adverse selection, Sharpe (1990), Rajan (1992), and von Thadden (2004) show that the inside information of borrowers gives relationship lenders an informational advantage over potential competitors. Hauswald and Marquez (2003) examine the impact of technological progress on the competition between two asymmetrically informed banks: an informed bank that can screen borrowers and an uninformed bank that does not have access to the screening technology. Hauswald and Marquez (2006) build a spatial model to analyze banks' strategic acquisition and use of proprietary information in credit market competition. We build on and extend their work to study the case in which both the banks and Fintech lender can screen borrowers and their signals are conditionally independent. This setup allows us to capture the prominent role of distinct information and technologies used in credit screening for the two types of lenders and examine the credit expansion view of Fintech lending through its use of alternative information. Banerjee (2005b) considers a two-lender model with asymmetric and independent screening to study banks' incentives to adopt new

[5]From an empirical perspective, Buchak, Matvos, Piskorski, and Seru (2018) show that, compared with non-Fintech lenders, Fintech lenders use substantially different information to set interest rates and serve more creditworthy borrowers. Fuster, Plosser, Schnabl, and Vickery (2019) find that Fintech default rates are approximately 25% lower than that of traditional lenders in the U.S. mortgage market, even though Fintech firms process mortgages faster. Tang (2019) provides evidence that P2P platforms compete with banks for the same borrower population. Cornaggia et al. (2019) document that commercial banks, especially small ones, experience decreasing personal loan volume and deteriorating loan quality with P2P lending platforms' emergence. De Roure, Pelizzon, and Thakor (2022) show that the riskiest borrowers migrate to P2P lenders when banks are faced with exogenously higher regulatory costs in Germany. Gopal and Schnabl (2022) also show that Fintech lending substitutes for bank lending. Balyuk, Berger, and Hackney (2020) provide evidence that Fintech lender's comparative advantage is more efficient processing of hard information. Using individual-level data in the personal credit market, Di Maggio and Yao (2021) find that Fintech lenders compete with banks for more creditworthy borrowers to increase their market shares and that Fintech borrowers have higher default rates than bank borrowers.

[6]More generally, the lending competition game is related to common-value auctions with asymmetrically informed bidders (see Milgrom and Weber (1982), Engelbrecht-Wiggans, Milgrom, and Weber (1983), Hausch (1987), Kagel and Levin (1999), and Banerjee (2005a)).

information technology.[7] Banerjee (2005b) focuses on the case that both lenders always offer credit upon seeing good signals. We extend the results of Banerjee (2005b) by considering the possibility that lenders do not bid even with good signals and fully characterizing the relationship between lenders' screening abilities and the competition equilibrium. This generalization is essential for analyzing how the lending competition outcome varies with the borrower's distance to the bank in our model.

The rest of this article is organized as follows: Section II presents the model. In Section III, we characterize a lending competition game between two asymmetrically informed lenders, which is used to analyze the competition between the banks and Fintech lender in the model. Section IV studies the effect of Fintech lending on credit access, interest rates, and social welfare and discusses the empirical predictions. Section V concludes the article. All proofs are in the Supplementary Material.

II. Model

There are three types of agents in the economy: a continuum of measure 1 of borrowers, two incumbent banks, and one potential entrant lender. All the agents are risk-neutral.

The borrowers are uniformly distributed along a circle with circumference 1, and a borrower is indexed by $j \in [0,1]$. The borrower that lives at the north pole of the circle is indexed by 0, and the indices increase clockwise. Each borrower has an investment project that requires one unit of the initial investment. The project yields R if it succeeds and 0 if it fails. There are two types of borrowers with different success probabilities q_j's: high-type borrowers succeed with certainty ($q_j = 1$), whereas low-type borrowers always fail ($q_j = 0$). The proportion of high-type borrowers is $q \in (0,1)$ of all the borrowers. The success probabilities and distribution of borrower types are common knowledge. Each borrower has no private resources and resorts to lenders for a loan, and lenders cannot observe a borrower's type. Following the literature (Hauswald and Marquez (2003), (2006), von Thadden (2004)), we assume that it is ex ante efficient to provide credit to a borrower.

Assumption 1. $qR \geq 1$.

The two incumbent banks are placed equidistantly on the perimeter of the circle, and a bank is indexed by $i \in \{1,2\}$. Without loss of generality, we assume that Bank 1 is located at the north pole and Bank 2 is located at the south pole of the circle. For borrower j, there exists a unique bank, which is at a distance of no more than $1/4$; this bank is denoted as $i(j)$ and must be borrower j's nearest bank. For borrowers living at $1/4$ and $3/4$, their nearest bank is defined to be Bank 1. Let x_j denote the distance of borrower j to its nearest bank.

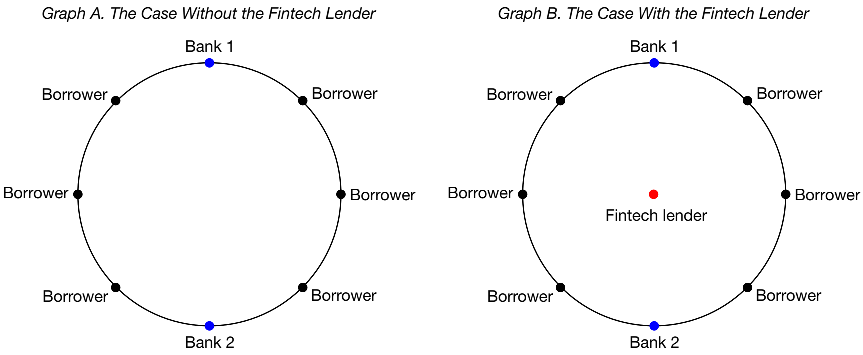
There is a potential entrant lender that adopts new Fintech technology. For example, this entrant lender could be a Bigtech firm such as Alibaba or Tencent.

[7]Broecker (1990) and Riordan (1993) consider lending competition with symmetric and independent screening.

FIGURE 1

Illustrations of the Circular City

Graph A of Figure 1 illustrates the circular city without the Fintech lender, and Graph B with the Fintech lender included.



We refer to the entrant as the Fintech lender, denoted by subscript F. If the Fintech lender enters, it will be placed at the center of the circle. Thus, the Fintech lender's distance to each borrower is the same (see Figure 1).

We assume that for borrower j, the nearest bank $i(j)$ can obtain signal $s_j \in \{g, b\}$ (g being a good signal and b being a bad signal), which provides the bank with proprietary information about the borrower's type. For example, the bank's loan officers can gather soft information about the applicant based on frequent interactions and in-depth interviews with the applicant. The bank may also have valuable information about the borrower from its previous lending relationship. In contrast, the borrower's farthest bank does not have access to such information and remains uninformed.[8] For simplicity, we refer to a borrower's nearest bank as its inside bank and the other as the outside bank.

Specifically, the inside bank's signal accuracy is

$$\phi(x_j) = \Pr(s_j = g | q_j = 1) = \Pr(s_j = b | q_j = 0).$$

Thus, the signal is correct with probability $\phi(x_j)$ and incorrect with probability $1 - \phi(x_j)$. This information structure is in line with that of Hauswald and Marquez (2003), (2006), and von Thadden (2004).

Assumption 2. ϕ is continuous and strictly decreasing in the bank–borrower distance.

This assumption captures the prominent role of geographical distance in bank lending, as documented by a large literature (see, e.g., Petersen and Rajan (2002), Degryse and Ongena (2005), Agarwal and Hauswald (2010), and Granja, Leuz, and

[8]We can relax this assumption by allowing the farthest bank to receive a noisy signal of the nearest bank's information. This would not change our main results (see Hauswald and Marquez (2003), von Thadden (2004)). The main idea is that if more than one bank screens the same borrower, their signals are conditionally dependent as all banks ultimately analyze the same data set. Thus, the bank with the inferior screening ability can only obtain a noisy signal of the nearest bank's screening outcome. Moreover, we can show that if screening is costly, the farthest bank will not acquire any information, which justifies our assumption in the model. See also Hauswald and Marquez (2006) for a similar argument.

Rajan (2022)).[9] As Petersen and Rajan (2002) argue, soft information is primarily of local nature. A bank's ability to produce soft information about borrowers has traditionally been based on its close interactions with potential borrowers (Liberti and Petersen (2019)). By facilitating the collection of soft information, borrower proximity enhances the bank's screening quality.

Denote $\underline{\phi} = \phi(1/4)$ and $\overline{\phi} = \phi(0)$ the lower and upper bounds of a bank's signal accuracy, respectively. We assume $\underline{\phi} > 1/2$ and $\overline{\phi} < 1$, which guarantees that a bank's signal is informative about a borrower's type but never fully revealing.

Assumption 3. $\underline{q}^b R < 1$, where $\underline{q}^b = \frac{q(1-\underline{\phi})}{q(1-\underline{\phi}) + (1-q)\underline{\phi}}$ is the probability that a project succeeds conditional on a bad signal at distance $1/4$.

Assumption 3 ensures that even for the farthest borrower, the inside bank's signal is so informative that a bad signal is sufficient to deem the project unprofitable. This assumption simplifies the model exposition and focuses our attention on the most relevant situations.

The Fintech lender is equipped with a technology that generates a binary signal $s_{F,j} \in \{g_F, b_F\}$ from screening borrower j. Unlike for banks, the Fintech lender's screening is based on the borrower's nontraditional information, such as digital footprints, rent and utilities bills, and social media activities.[10] To capture the fact that banks and Fintech lenders use different sets of data for their credit scoring and lending decisions, we assume that for a borrower, the signals of the inside bank and the Fintech lender are conditionally independent. Moreover, we assume that the Fintech lender's screening applies uniformly to all borrowers. Specifically,

$$\phi_F = \Pr(s_{F,j} = g_F | q_j = 1) = \Pr(s_{F,j} = b_F | q_j = 0).$$

A natural interpretation of this assumption is that interactions between borrowers and the Fintech lender are virtual. For example, borrowers apply for loans from the Fintech lender mainly through mobile phones or the Internet. Hence, the Fintech lender's screening depends less on physical distance compared to that of traditional banks.

Assumption 4. $\overline{\phi} > \phi_F > \underline{\phi}$.

Together with Assumptions 2 and 3, Assumption 4 provides a convenient way to capture the comparative advantage of banks and Fintech lenders in different market segments. On the one hand, compared with the Fintech lender, banks are better informed about their nearest borrowers than the Fintech lender is. This reflects that banks have an informational advantage in their specialized markets compared with the Fintech lender. For instance, banks may be more able to collect

[9] Almazan (2002) and Vives and Ye (2021) also study bank competition within a spatial competition framework (Salop (1979)).

[10] For empirical evidence, see, e.g., Iyer et al. (2016), Frost et al. (2019), Fuster et al. (2019), Jagtiani and Lemieux (2019), Agarwal et al. (2020), and Berg et al. (2020). There is no doubt that banks can also benefit from using big data analytics and alternative data. However, several factors, such as legacy technology, security concerns, and regulations, constrain a bank's ability to adopt new technologies (see Boot, Hoffmann, Laeven, and Ratnovski (2021) for a discussion).

soft information about a borrower with close interactions, which cannot be identified through a purely digital channel.[11] On the other hand, as the distance between a bank and borrowers increases, the bank's soft information quality deteriorates. In contrast, Fintech lenders can better mitigate the information asymmetry by leveraging big data analytics with abundant alternative data.[12] In this case, the Fintech lender may have an informational advantage over banks. Overall, this setup allows us to consider borrowers with heterogeneous relationships with banks and Fintech lenders in a simple way.

Following the literature (Broecker (1990), Hauswald and Marquez (2003), (2006), von Thadden (2004), and Banerjee (2005b)), we assume that each borrower can borrow from at most one lender. We also assume that each lender's decision (acceptance or rejection) is unobservable to the other lenders. The timing of the game is as follows. First, each borrower applies for a loan from the lenders in the market. Then, the lenders screen the borrower and obtain private signals of the borrower's creditworthiness. Conditional on the screening outcome, the lenders simultaneously decide whether to provide credit to the applicant and the gross interest rate $r \in [1, R]$, i.e., the gross repayment to the lender if the project succeeds. If multiple lenders offer credit to a borrower, then the borrower accepts the loan contract with the lowest interest rate. If multiple lenders quote the same interest rate, then the borrower chooses between them with equal probability.[13] After a borrower is funded, the outcome of the project is realized and publicly observed; the borrower pays the gross interest rate if the project succeeds and 0 otherwise. If a borrower does not receive any offer, the payoff is 0. For simplicity, we assume that the cost of funding for both the banks and Fintech lender is 1.[14]

In the following sections, we analyze the impacts of Fintech lending by comparing the equilibrium under two different credit markets—without and with Fintech lending. As will become clear in Section IV, the key to analyzing the market competition with Fintech lending is to solve the equilibrium of a lending competition between a borrower's inside bank and the Fintech lender. Therefore, we proceed in two steps. First, Section III characterizes the lending competition equilibrium between two asymmetrically informed lenders with conditionally

[11]Di Maggio and Yao (2021) find that Fintech lenders predominantly rely on hard information to make credit decisions, much more than traditional lenders. Balyuk et al. (2020) also note that the Fintech lender's comparative advantage lies in more efficient processing of hard information. Huang et al. (2020) show that the screening technology of a Bigtech lender in China predicts loan defaults during normal times better than does that of banks.

[12]For example, Fuster et al. (2019) document that Fintech lenders have lower default rates than traditional lenders in the U.S. mortgage market. Agarwal et al. (2020) and Berg et al. (2020) find that easily accessible variables from customers' digital footprints are better than credit scores at predicting loan default.

[13]Equivalently, the lending competition can be described as such: each borrower can approach lenders sequentially, keeping each lender's decision unobserved to the other lenders, and then decide to accept a loan offer if she has got any after applying to all the lenders.

[14]A more realistic assumption may be that the Fintech lender has a disadvantage in funding costs due to various factors, such as the absence of a safety net. However, given that our focus is on the differences in the screening technologies used by traditional banks and the Fintech lender, the inclusion of asymmetric funding costs only complicates the analysis and diverts from our main focus on information asymmetry.

independent signals. Second, we use the results derived in Section III to characterize the market equilibrium with Fintech lending and study its effect on credit access, expected interest rates, and social welfare in Section IV.

III. The Analysis of a Two-Lender Competition Game

Section III presents a result of a lending competition game between two asymmetrically informed lenders with independent signals. It extends the findings in the literature. On the one hand, Hauswald and Marquez (2003), (2006), and von Thadden (2004) study the competition between one informed and one uninformed lender.[15] On the other hand, Broecker (1990) considers lending competition with symmetric and independent screening. Banerjee (2005b) studies an asymmetric lending competition model for the special case in which the lenders always bid after receiving good signals. We apply the results derived here to study the equilibrium in a credit market with Fintech lending in Section IV.

In Section III, borrowers' heterogeneity in location is ignored. There are two lenders, both of which can obtain informative signals from screening. We assume that one lender obtains signal $s_j \in \{g, b\}$ and the other acquires signal $\tilde{s}_j \in \{\tilde{g}, \tilde{b}\}$ by screening borrower j. The signal accuracy of s_j and $\tilde{s}_j$, respectively, is as follows:

$$\phi = \Pr(s_j = g | q_j = 1) = \Pr(s_j = b | q_j = 0),$$
$$\tilde{\phi} = \Pr(\tilde{s}_j = \tilde{g} | q_j = 1) = \Pr(\tilde{s}_j = \tilde{b} | q_j = 0).$$

Without loss of generality, we assume that $1/2 < \tilde{\phi} \leq \phi < 1$; i.e., lenders are asymmetrically informed. The lender with signal accuracy ϕ is the *more informed* lender, and the lender with signal accuracy $\tilde{\phi}$ is the *less informed* lender.

Before analyzing the model, we introduce some notation to simplify the exposition. Let A be the realization of signals about a borrower's type. For example, $A = b\tilde{g}$ means that a bad signal is observed by the more informed lender, i.e., $s_j = b$, and a good signal is observed by the less informed lender, i.e., $\tilde{s}_j = \tilde{g}$, from screening borrower j.

Let $p^A = \Pr(A)$ denote the probability of A, for example,

$$p^g = \Pr(s_j = g) = q\phi + (1-q)(1-\phi),$$
$$p^{g\tilde{b}} = \Pr(s_j = g, \tilde{s}_j = \tilde{b}) = q\phi(1-\tilde{\phi}) + (1-q)(1-\phi)\tilde{\phi}.$$

Let B be another realization of signals and $P_B^A = \Pr(A|B)$ denote the probability of A conditional on B, for example,

$$P_g^{\tilde{b}} = \Pr(\tilde{s}_j = \tilde{b} | s_j = g) = p^{g\tilde{b}} / p^g.$$

Let $q^A = \Pr(\text{success}|A)$ denote the probability of succeeding conditional on A, for example,

[15]Hauswald and Marquez (2003) and von Thadden (2004) also consider the case wherein the uninformed lender receives a noisy signal of the more informed lender's screening outcome, and they obtain similar results.

$$q^g = \Pr(\text{success}|s_j = g) = q\phi/p^g,$$
$$q^{g\tilde{b}} = \Pr(\text{success}|s_j = g, \tilde{s}_j = \tilde{b}) = q\phi(1-\tilde{\phi})/p^{g\tilde{b}}.$$

Last, let $\bar{r} = 1/q$ denote the break-even interest rate without additional information, and let $r^A = 1/q^A$ denote the break-even interest rate conditional on A.

Analogous to Assumption 3, we assume that $q^{\tilde{b}}R < 1$; that is, the less informed lender has a sufficiently informative signal such that a borrower can be deemed unprofitable based on a bad signal from screening. This assumption is also equivalent to a restriction on the magnitude of the project return. Along with Assumption 1, this requires that $\bar{r} \leq R < r^{\tilde{b}}$.

One interesting feature of the lending competition games is the phenomenon of winner's curse—winning a borrower reveals that other lenders are very likely to receive bad signals and reject the borrower. Because of the winner's curse, pure-strategy Nash equilibrium typically does not exist (Broecker (1990), Hauswald and Marquez (2003), (2006), von Thadden (2004), and Banerjee (2005b)).[16] We prove that this is also the case with two asymmetrically informed lenders.

Lemma 1. There is no pure-strategy equilibrium in the lending competition game.
Proof. In the Supplementary Material.

The reasoning is as follows. Suppose there is such an equilibrium in which lenders offer different rates upon seeing a good signal. Then, the lender that offers a lower rate will always want to deviate by slightly increasing its rate to earn more without hurting its average loan quality. Hence, lenders must offer the same interest rate. However, if two lenders offer the same rate, the less informed lender must offer a rate that is higher than its break-even rate $r^{\tilde{g}}$ due to the winner's curse. Then the more informed lender always has an incentive to undercut the less informed lender. These observations rule out the existence of a pure-strategy Nash equilibrium.

However, there exists a unique mixed-strategy Nash equilibrium. A mixed strategy in this lending competition game has two components: the *rejection probability*, which is the probability of rejecting a loan application conditional on a good signal, and the *interest rate strategy*, which is the distribution of interest rates if the loan application is accepted. Let (z, G) denote the more informed lender's strategy, where z is the rejection probability and G is the interest rate strategy. Similarly, the less informed lender's strategy is denoted by $(\tilde{z}, \tilde{G})$. Given a strategy profile, let $V(r)$ and $\tilde{V}(r)$ be the more and the less informed lender's expected profits from quoting interest rate r to a borrower conditional on a good signal, respectively,

$$\text{(1)} \qquad V(r) = P_g^{\tilde{b}}\left(q^{g\tilde{b}}r - 1\right) + P_g^{\tilde{g}}\left[1 - (1-\tilde{z})\tilde{G}(r)\right]\left(q^{g\tilde{g}}r - 1\right)$$
$$= (q^g r - 1) - (1-\tilde{z})\tilde{G}(r)P_g^{\tilde{g}}\left(q^{g\tilde{g}}r - 1\right),$$

[16]More generally, this is related to the common-value auctions literature (e.g., Engelbrecht-Wiggans et al. (1983)).

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$$\tag{2} \begin{aligned}\tilde{V}(r) &= P^b_{\tilde{g}}\left(q^{b\tilde{g}}r-1\right)+P^g_{\tilde{g}}[1-(1-z)G(r^-)]\left(q^{g\tilde{g}}r-1\right)\\ &= \left(q^{\tilde{g}}r-1\right)-(1-z)G(r^-)P^g_{\tilde{g}}\left(q^{g\tilde{g}}r-1\right).\end{aligned}$$

Note that there is a positive mass for G, as we prove later. We define the equilibrium of such a competition between two asymmetrically informed lenders as follows:

Definition 1. An equilibrium is a strategy profile $\left((z,G),(\tilde{z},\tilde{G})\right)$ such that i) given $\left(\tilde{z},\tilde{G}\right)$, z and almost every $r\in\operatorname{supp}G$ maximize $V(r)$ and ii) given (z,G), $\tilde{z}$ and almost every $r\in\operatorname{supp}\tilde{G}$ maximize $\tilde{V}(r)$.

Let us first define a cut-off value $\phi^\star=[(qR-1)/(1-q)+1/\phi]^{-1}$ for the less informed lender. The following proposition fully characterizes the equilibrium of the lending competition:

Proposition 1. There exists a unique mixed-strategy equilibrium $\left((z,G),(\tilde{z},\tilde{G})\right)$ as follows:

(i) Suppose $\tilde{\phi}\le\phi^\star$. Then, the more informed lender accepts all loan applications with a good signal, i.e., $z=0$, and the less informed lender rejects loan applications with probability $\tilde{z}=1-q^g\left(R-r^{\tilde{g}}\right)/P^{\tilde{g}}_g\left(q^{g\tilde{g}}R-1\right)$ conditional on a good signal. If a loan application is accepted, then the interest rates offered by the more and the less informed lender are drawn from the distribution G and $\tilde{G}$, respectively, where G and $\tilde{G}$ have a common support $\left[r^{\tilde{g}},R\right]$, and, for any $r\in\left[r^{\tilde{g}},R\right)$,

$$G(r)=\frac{q^{\tilde{g}}r-1}{P^g_{\tilde{g}}(q^{g\tilde{g}}r-1)}\ \text{and}\ \tilde{G}(r)=\frac{q^{g\tilde{g}}R-1}{q^g\left(R-r^{\tilde{g}}\right)}\frac{q^g\left(r-r^{\tilde{g}}\right)}{q^{g\tilde{g}}r-1}.$$

The expected profits of the more and the less informed lender are given by

$$v=(1-q)\left(\phi/\tilde{\phi}-1\right)\ \text{and}\ \tilde{v}=0.$$

(ii) Suppose $\tilde{\phi}>\phi^\star$. Then, both lenders accept all loan applications with a good signal, i.e., $z=\tilde{z}=0$, and the interest rates offered by the more and the less informed lender are drawn from the distribution G and $\tilde{G}$, respectively, where G and $\tilde{G}$ have a common support $[r',R]$ with $r'=R-P^{\tilde{g}}_g\left(q^{g\tilde{g}}R-1\right)/q^g$, and, for any $r\in[r',R)$,

$$G(r)=\frac{q^{\tilde{g}}(r-r')}{P^g_{\tilde{g}}(q^{g\tilde{g}}r-1)}\ \text{and}\ \tilde{G}(r)=\frac{q^g(r-r')}{P^{\tilde{g}}_g(q^{g\tilde{g}}r-1)}.$$

The expected profits of the more and the less informed lender are given by

$$\begin{aligned}&v=\phi\left(1-\tilde{\phi}\right)q(R-1)-(1-\phi)\tilde{\phi}(1-q)\ \text{and}\\ &\tilde{v}=\tilde{\phi}\left(1-\tilde{\phi}\right)\left[(qR-1)+(1-q)\left(\phi^{-1}-\tilde{\phi}^{-1}\right)\right].\end{aligned}$$

Proof. In the Supplementary Material.

Remark 1. If $\phi > \tilde{\phi} > \phi^\star$, $v > \tilde{v} > 0$. If $\phi = \tilde{\phi}$, $v = \tilde{v} = \phi(1-\phi)(qR-1)$.

Remark 2. We can verify that the equilibrium is continuous at $\phi^\star$. That is, $\lim_{\tilde{\phi}\uparrow\phi^\star}\tilde{z} = 0$; $\lim_{\tilde{\phi}\uparrow\phi^\star} r^{\tilde{g}} = \lim_{\tilde{\phi}\downarrow\phi^\star} r'$; $\lim_{\tilde{\phi}\uparrow\phi^\star} G = \lim_{\tilde{\phi}\downarrow\phi^\star} G$ and $\lim_{\tilde{\phi}\uparrow\phi^\star}\tilde{G} = \lim_{\tilde{\phi}\downarrow\phi^\star}\tilde{G}$; $\lim_{\tilde{\phi}\uparrow\phi^\star} v = \lim_{\tilde{\phi}\downarrow\phi^\star} v$ and $\lim_{\tilde{\phi}\downarrow\phi^\star}\tilde{v} = 0$.

We prove Proposition 1 by a series of lemmas in the Supplementary Material. Note that $\tilde{\phi} \le \phi^\star$ is equivalent to $1/\tilde{\phi} - 1/\phi \ge (qR-1)/(1-q)$, wherein $1/\tilde{\phi} - 1/\phi$ can be considered a measure of the screening ability gap between the more and the less informed lender. Thus, the proposition states that the equilibrium crucially depends on the screening ability gap between the two lenders.

If $\tilde{\phi} \le \phi^\star$, the screening ability gap is large. The less informed lender faces a strong winner's curse when competing with the more informed lender. In equilibrium, the less informed lender is indifferent to making an offer—it rejects a fraction of the loan applications with a good signal and obtains 0 expected profits. Moreover, we can prove that the rejection probability $\tilde{z}$ increases with the more informed lender's screening accuracy. In contrast, the more informed lender always makes an offer upon seeing a good signal. Because of its informational advantage over the less informed competitor, the more informed lender can extract rents from borrowers with good signals and make positive expected profits. In this case, the strategies of the less and the more informed lender are similar to those of Hauswald and Marquez (2003), (2006), and von Thadden (2004).[17] In fact, when $\tilde{\phi} = 1/2$, that is, when the less informed lender's signal is uninformative, the equilibrium is the same as that in Hauswald and Marquez (2006).[18]

Conversely, if $\tilde{\phi} > \phi^\star$, the screening ability gap between the two lenders is small. Therefore, the winner's curse becomes less severe for the less informed lender. In this case, both lenders always offer credit upon seeing good signals in equilibrium. Banerjee (2005b) obtains the same result under a sufficient assumption (Assumption 3 in that article), which guarantees that the project returns are sufficiently high such that both lenders' expected profits from bidding are positive. Our model extends the result of Banerjee (2005b) by relaxing this assumption and allowing for the possibility that lenders reject loan applications with good signals. In doing so, we derive a necessary and sufficient condition, in terms of the lenders' screening abilities ($\tilde{\phi} > \phi^\star$), for both lenders to bid with good signals in equilibrium. Thus, Proposition 1 establishes a clear relationship between lenders' screening abilities and the competition outcome. With this result, we can analyze the lending competition equilibrium and the effect of Fintech lending for borrowers with different distances to the banks in the spatial model.

[17]He et al. (2023) also consider a lending competition between two asymmetrically informed lenders. With a different "bad-news" information structure (a good borrower always generates a good signal, whereas a bad borrower may generate either a good or bad signal), they show that a weak lender with less accurate screening always earns 0 expected profits when competing with a strong lender and rejects borrowers upon seeing a good signal with a positive probability. Their result is consistent with ours when the less informed lender's screening accuracy is below the key cut-off $\phi^\star$.

[18]We have to be cautious with this observation because $\tilde{\phi} = 1/2$ means that the assumption $q^{\tilde{b}} R < 1$ is violated.

Note that the cut-off $\phi^\star$ depends on the average profitability of borrowers and the more informed lender's screening accuracy. First, $\phi^\star$ decreases with the average profitability of borrowers. A higher average profitability of borrowers alleviates the problem of adverse selection; thus, the less informed lender can make positive expected profits with a lower minimum screening accuracy. Second, $\phi^\star$ increases with the more informed lender's screening accuracy. The winner's curse becomes more severe as the more informed lender's screening improves. Consequently, the minimum screening accuracy that guarantees positive expected profits for the less informed lender must increase.

The following result shows that the more informed lender is more likely to offer a high interest rate than the less informed lender.

Corollary 1. The more informed lender's interest rate strategy, first-order stochastically dominates (FOSD) the less informed lender's, i.e., $G(r) \leq \tilde{G}(r)$, in the equilibrium.

Proof. In the Supplementary Material.

Intuitively, the more informed lender knows that its screening accuracy is higher than that of the less informed lender, so it does not worry too much about the winner' s curse and bids less aggressively. For example, the more informed lender extends credit on interest rate R with a strictly positive mass, i.e., $G(R^-) < 1$, while the less informed lender offers interest rate R with probability 0, i.e., $\tilde{G}(R^-) = 1$, in general.[19]

Next, we consider the effect of signal accuracy on the two lenders' expected profits. The results are summarized in the following corollary, and we omit the proof as it immediately follows from Proposition 1.

Corollary 2. (i) If $\tilde{\phi} \leq \phi^\star$ holds, the more informed lender's expected profits increase as its signal accuracy increases or its rival's signal accuracy decreases. (ii) If $\tilde{\phi} > \phi^\star$ holds, the more informed lender's expected profits increase as its signal accuracy increases or its rival's signal accuracy decreases. The less informed lender's expected profits increase as its rival's signal accuracy decreases.

If $\tilde{\phi} \leq \phi^\star$, the screening ability gap becomes larger as the more informed lender's signal accuracy increases or its rival's signal accuracy decreases. Thus, the less informed lender suffers a greater degree of adverse selection. The more informed lender bids less aggressively and earns higher expected profits.[20]

Similarly, if $\tilde{\phi} > \phi^\star$, the more informed lender's expected profits increase with the screening ability gap. However, for the less informed lender, an improvement in its screening accuracy may not necessarily increase its profits. When $\tilde{\phi}$ increases, the less informed lender can better select creditworthy borrowers. On the one hand, it suffers less from the winner's curse. On the other hand, the two lenders compete

[19]Note that $G(R^-) = \lim_{r \uparrow R} G(r)$ and $\tilde{G}(R^-) = \lim_{r \uparrow R} \tilde{G}(r)$. Moreover, $G(R^-) = 1$, if and only if $\phi = \tilde{\phi}$.

[20]In a lending competition game between an informed lender and an uninformed lender, Hauswald and Marquez (2003) also shows that the informed lender's expected profit increases as its signal accuracy increases.

more aggressively for borrowers, which intensifies competition and negatively affects the less informed lender's expected profits. Overall, the effect of improving screening accuracy on the less informed lender is ambiguous.

IV. Fintech Lending

In Section IV, we study the effect of Fintech lending on access to credit, interest rates, and social welfare. First, we briefly illustrate the equilibrium in a credit market with two existing banks, which corresponds to the case without Fintech lending. Then, we characterize the new equilibrium with Fintech lending using the results derived in Section III. Finally, we compare the two equilibriums and analyze the impact of Fintech lending.

A. Market Without Fintech Lending

Without Fintech lending, the two incumbent banks compete for borrowers. For a given borrower, the nearest bank is the inside bank, which obtains an informative signal about the borrower, while the outside bank is uninformed. Consequently, the lending competition is between two asymmetrically informed banks: one is informed and the other is uninformed.

As shown in Hauswald and Marquez (2003), (2006), and von Thadden (2004), there is no pure-strategy Nash equilibrium because of the winner's curse. However, there exists a unique mixed-strategy Nash equilibrium. Let z and G denote the probability of rejecting loan applications and the distribution of interest rates offered by the inside bank upon a good signal, and let z_u and G_u denote the probability of rejecting loan applications and the distribution of interest rates offered by the outside bank. We define the equilibrium of this lending competition game as follows.

Definition 2. For a given borrower, an equilibrium in the lending competition between the inside and outside banks consists of $((z,G),(z_u,G_u))$ such that they satisfies the following conditions:

(i) Given z_u and G_u, z and almost every interest rate $r \in \mathrm{supp}G$ maximize the expected profits of the inside bank conditional on a good signal.

(ii) Given z and G, z_u and almost every interest rate $r \in \mathrm{supp}G_u$ maximize the expected profits of the outside bank.

Then, the following proposition summarizes the equilibrium:

Proposition 2 (Hauswald and Marquez (2006)). For a given borrower located at a distance x from its inside bank, there exists a unique mixed-strategy equilibrium in the competition between the two banks. In the equilibrium, i) the inside bank makes positive expected profits $\widehat{v}(x)=(1-q)[2\phi(x)-1]$, and the outside bank makes 0 expected profits; ii) the inside bank always offers credit upon seeing a good signal, i.e., $z=0$, and the outside bank rejects the borrower with probability $z_u=(q^g\overline{r}-1)/(q^gR-1)$. The interest rate distributions G and G_u have a common support $[\overline{r},R]$, and, for any $r\in[\overline{r},R)$,

(3) $$G(r) = \frac{qr-1}{p^g(q^g r-1)},$$

(4) $$G_u(r) = \frac{q^g R-1}{R-\overline{r}} \frac{r-\overline{r}}{q^g r-1}.$$

We refer to the *captive market* of bank i as the region where borrowers' nearest bank is bank i. Each bank earns positive expected profits from extending loans to the borrowers in its captive market. In the model, the arc length between a bank and the farthest borrower in its captive market is $1/4$. For any borrower at distance $x<1/4$, its nearest bank acts as an inside bank—this bank will make an offer upon seeing a good signal and earn positive expected profits of $\widehat{v}(x) = (1-q)[2\phi(x)-1]$. However, outside of its captive market, a bank plays the role of an outside lender and earns 0 expected profits. Hence, the gross expected profits of each bank is $\widehat{\Omega} = 2\int_0^{1/4} \widehat{v}(x)dx$. By symmetry, the expected profit applies to both banks, so the subscript i is omitted.

B. Market with Fintech Lending

Upon entry, the Fintech lender competes directly with the two incumbent banks. Now, a borrower can apply for loans from three lenders. The inside bank and Fintech lender are informed, and they have conditionally independent signals with an accuracy of $\phi(x)$ and ϕ_F, respectively, while the outside bank is uninformed. Note that depending on the borrower's location, the inside bank may be better or less informed than the Fintech lender, i.e., $\phi(x) \geq \phi_F$ or $\phi(x) < \phi_F$. Hence, we characterize the equilibrium of the credit market competition with three lenders: a more informed, a less informed, and an uninformed lender.

To be consistent with the exposition in Section III, let ϕ and $\tilde{\phi}$ denote the signal accuracy of the more and the less informed lender, respectively. Again, we focus on the mixed-strategy equilibrium, as it can be similarly argued that no pure-strategy equilibrium exists. Let $\left((z,G),(\tilde{z},\tilde{G}),(z_u,G_u)\right)$ denote a profile of lenders' strategies, where (z,G) and $\left(\tilde{z},\tilde{G}\right)$ are the two informed lenders' strategies upon observing a good signal as denoted in Section III, and (z_u,G_u) is the uninformed bank's (unconditional) strategy. Given the lenders' strategies, $V(r)$ and $\tilde{V}(r)$ denote the more and the less informed lender's expected profits, respectively, from offering a loan contract with interest rate r conditional on a good signal; $V_u(r)$ denotes the uninformed bank's expected payoff from offering a loan contract with interest rate r to a borrower.

Definition 3. An equilibrium is a strategy profile $\left((z,G),(\tilde{z},\tilde{G}),(z_u,G_u)\right)$ such that:

(a) Given $\left(\tilde{z},\tilde{G}\right)$ and (z_u,G_u), z and almost every $r \in \text{supp}G$ maximize $V(r)$.
(b) Given (z,G) and (z_u,G_u), $\tilde{z}$ and almost every $r \in \text{supp}\tilde{G}$ maximize $\tilde{V}(r)$.
(c) Given (z,G) and $\left(\tilde{z},\tilde{G}\right)$, z_u and almost every $r \in \text{supp}G_u$ maximize $V_u(r)$.

The following proposition characterizes the equilibrium of the lending competition with three asymmetrically informed lenders:

Proposition 3. For a given borrower, there exists a unique equilibrium in the competition between the two banks and the Fintech lender. In the equilibrium, the outside bank always rejects loan applications, i.e., $z_u = 1$, while the bidding strategies of the two informed lenders (the inside bank and the Fintech lender) are the same as those described in Proposition 1.
Proof. In the Supplementary Material.

Proposition 3 states that the lending competition between the three lenders can be degenerated into a lending competition game between the inside bank and the Fintech lender. We can understand this result as follows. As the inside bank and Fintech lender have private information about the borrowers, they can offer interest rates lower than the break-even interest rate $\bar{r}$ upon observing a good signal and still earn positive profits. However, the outside bank can never offer an interest rate lower than $\bar{r}$; otherwise, it will incur a loss. If a borrower accepts the outside bank's offer, it is likely to be rejected by the other two informed lenders. Thus, the outside bank faces two winner's curse problems. The outside bank always makes an expected loss if a borrower accepts the offer, and consequently, refrains from bidding to avoid loss.[21] Put differently, the entry of the Fintech lender crowds out the outside bank.

This result is essentially the same as the findings of Dell'Ariccia, Friedman, and Marquez (1999). In their model, a new bank intends to enter a credit market with two incumbent banks. Each incumbent bank perfectly (and privately) knows the creditworthiness of a fraction of the old borrowers. The potential entrant faces adverse selection because it cannot distinguish between new and old borrowers who have been rejected by the incumbent banks. Dell'Ariccia et al. (1999) show that the potential entrant incurs a loss upon entry, so it never enters the market even in the absence of any sunk entry costs. Although the setup of the two models is different, both articles suggest that the informational advantage of the informed lenders may block the entry of a potential uninformed competitor.

The following proposition illustrates how Fintech lending affects the incumbent banks in terms of profits:

Proposition 4. After the Fintech lender's entry, each bank's expected profits decrease.
Proof. In the Supplementary Material.

There are two channels through which a bank's expected profits are affected. First, the informational advantage of the inside bank is lowered after the Fintech lender enters. Consequently, the inside bank chooses to offer lower interest rates in response to the increased competition. Second, a bank's captive market wherein it makes positive profits may effectively shrink after the Fintech lender's entry.

[21]This result is most evident when we consider the case whereby the less informed lender makes 0 expected profits in equilibrium. As the outside bank is in an even worse informational situation than the less informed lender, it can only make a negative expected profit.

Suppose a borrower is far away from the nearest bank. Then, the Fintech lender may have a more accurate signal from screening the borrower than the inside bank does. Furthermore, if the inside bank's signal accuracy is lower than a certain cut-off, it may reject the borrower even upon seeing a good signal and make 0 expected profits, as we show in Proposition 1. Therefore, the bank's effective captive market becomes smaller. As these two channels work in the same direction, Fintech lending unambiguously reduces the incumbent banks' expected profits.

C. Fintech Lending and Credit Access

In Section IV.C, we analyze the implications of Fintech lending for borrowers' access to credit. Our key insight is that there is an extensive vs. intensive trade-off associated with Fintech lending—the Fintech lender's entry increases the number of lenders in the market, providing borrowers with more options for obtaining credit; however, it also leads to adverse selection for the existing banks and decreases their credit supply. The overall effect depends on the relative magnitude of the extensive increase and intensive decrease effects, which in turn are determined by the type of borrowers and their distance to the inside bank.

We fix a borrower at a distance x from its inside bank and call it *borrower x*. The borrower's credit availability is defined as the probability of receiving at least one offer. We analyze whether Fintech lending increases high-type borrowers' credit availability and decreases low-type borrowers' credit availability. The findings are summarized in the following proposition:

Proposition 5. Consider a given borrower located at a distance x from its inside bank.

(i) If the Fintech lender's signal is less accurate than the inside bank's signal, i.e., $\phi_F \leq \phi(x)$, then, after the Fintech lender's entry, 1) a high-type borrower's credit availability always increases, and 2) a low-type borrower's credit availability increases when the Fintech lender's signal is not so informative, i.e., $\phi_F \leq [(qR-1)/(1-q)+1/\phi(x)]^{-1}$.

(ii) If the Fintech lender's signal is more accurate than the inside bank's signal, i.e., $\phi_F > \phi(x)$, then, after the Fintech lender's entry, a high-type borrower's credit availability increases when the inside bank's signal is sufficiently accurate, i.e., $\phi(x) \geq [(qR-1)/(1-q)+1/\phi_F]^{-1}$. Otherwise, there exist parameters such that a high-type borrower's credit availability decreases after the Fintech lender's entry.

Proof. In the Supplementary Material.

Proposition 5 indicates that for a given borrower, the effect of Fintech lending on credit availability depends on the type of the borrower and its distance to the inside bank. That is, there is heterogeneity in terms of how Fintech lending affects borrowers. Most interestingly, the entry of the Fintech lender can either increase or decrease a high-type borrower's credit access. This result suggests that we should be cautious of the widely held view that Fintech lending will necessarily expand credit access to those borrowers with observably poor but actually good credit.

To interpret this result intuitively, consider a borrower that is close to the inside bank. Without Fintech lending, the inside bank makes an offer upon seeing a good signal and the outside bank makes an offer with a positive probability. With Fintech lending, the outside bank refrains from bidding and the inside bank and Fintech lender bid for borrowers upon seeing a good signal, as stated in Proposition 3. Clearly, Fintech lending generates two opposing effects on borrowers' credit access. On the one hand, there is an extensive increase effect because the Fintech lender extends credit to a borrower as long as it obtains a good signal. The borrower is more likely to pass a lender's creditworthiness test and obtain credit. Moreover, the extensive effect is affected by the borrower's type. Intuitively, a high-type borrower benefits more from an improvement in the Fintech lender's screening accuracy than a low-type borrower does. On the other hand, there is an intensive decrease effect because the outside bank decreases its credit supply due to the fear of adverse selection. Our parameter assumptions (particularly, Assumptions 3 and 4) guarantee that, overall, the Fintech lender's signal is sufficiently informative, and for a high-type borrower, the extensive increase effect exceeds the intensive decrease effect. Thus, a high-type borrower is more likely to obtain credit with Fintech lending. For the low-type borrowers, the Fintech lender replaces the outside bank in providing credit. If the Fintech lender's signal is not sufficiently informative, a low-type borrower has a high probability of being erroneously identified as a high-type borrower by the Fintech lender and obtaining credit. Consequently, it is possible that the extensive increase effect dominates the intensive decrease effect and a low-type borrower's credit availability increases with Fintech lending.

Then, consider a high-type borrower far from its inside bank. In this case, the inside bank's screening accuracy is relatively low. This implies that before the Fintech lender's entry, the outside bank does not face a severe winner's curse. Hence, it is possible that the outside bank makes an offer to the borrower with a high probability. Upon the entry of the Fintech lender with a superior screening technology, the inside bank could become informationally disadvantaged against the Fintech lender. Therefore, it may reject a borrower even upon seeing a good signal, as stated in Propositions 1 and 3. Furthermore, the outside bank refrains from bidding. In this case, for a high-type borrower, both the extensive increase and intensive decrease effects increase with the Fintech lender's screening ability. On the one hand, a high-type borrower is more likely to generate a good signal as the Fintech lender's screening improves. On the other hand, the winner' s curse is more severe for the existing banks. However, the Fintech lender's screening accuracy increases the extensive effect linearly, while it has a diminishing marginal impact on the intensive decrease effect. Consequently, when the Fintech lender's screening accuracy is sufficiently high, the extensive increase effect exceeds the intensive decrease effect. Otherwise, the intensive decrease effect can dominate the extensive increase effect and Fintech lending reduces a high-type borrower's credit availability. In recent work, He et al. (2023) find that open banking can reduce high-quality borrowers' welfare if the Fintech lender's signal becomes more accurate than the bank's signal. While they focus on interest rates, our results speak to the effect of Fintech lending on credit access.

Most articles in the prior literature find that the entry of a new lender increases credit availability. For example, Broecker (1990) shows that when there are more banks in the market, a borrower is more likely to obtain credit as its probability of passing a creditworthiness test increases. This extensive increase effect appears in our model too. However, there is a countervailing effect as well—by generating an information externality, the Fintech lender can lead the outside bank to quit the competition and decrease the inside bank's probability of bidding upon seeing a good signal. That is, the Fintech lender's entry may crowd out the existing banks' credit supply, as documented in Cornaggia et al. (2019). The mechanism driving our results is also different from that of Petersen and Rajan (1995). In the two-period model of Petersen and Rajan (1995), banks with market power can extract future surpluses from a firm to subsidize credit at the beginning of the relationship and more competition undermines banks' ability to cross-subsidize and may reduce borrowers' credit access. In contrast, we obtain our result in a one-period model wherein lenders' screening imposes an information externality on the competitors.

D. Fintech Lending and Expected Interest Rates

Section IV.D analyzes the impacts of Fintech lending on the cost of credit. By Proposition 3, there will always be two active lenders that are likely to extend credit to a borrower, before or after the Fintech lender's entry. For borrower x, denote r_M and r_L the interest rate offered by the more and the less informed lender, respectively. Let G_M and G_L denote the distribution functions of r_M and r_L, respectively. Moreover, let r_B denote the interest rate accepted by the borrower, i.e., $\min\{r_M, r_L\}$, if both lenders offer credit. Because both active lenders bid simultaneously and G_M and G_L are independent, the distribution of r_B is $G_B = 1 - (1 - G_M)(1 - G_L)$.

Proposition 6. If $\phi_F \leq \phi(x)$, the expected interest rates, $E(r_M)$, $E(r_L)$, and $E(r_B)$, decrease after the Fintech lender's entry.
Proof. In the Supplementary Material.

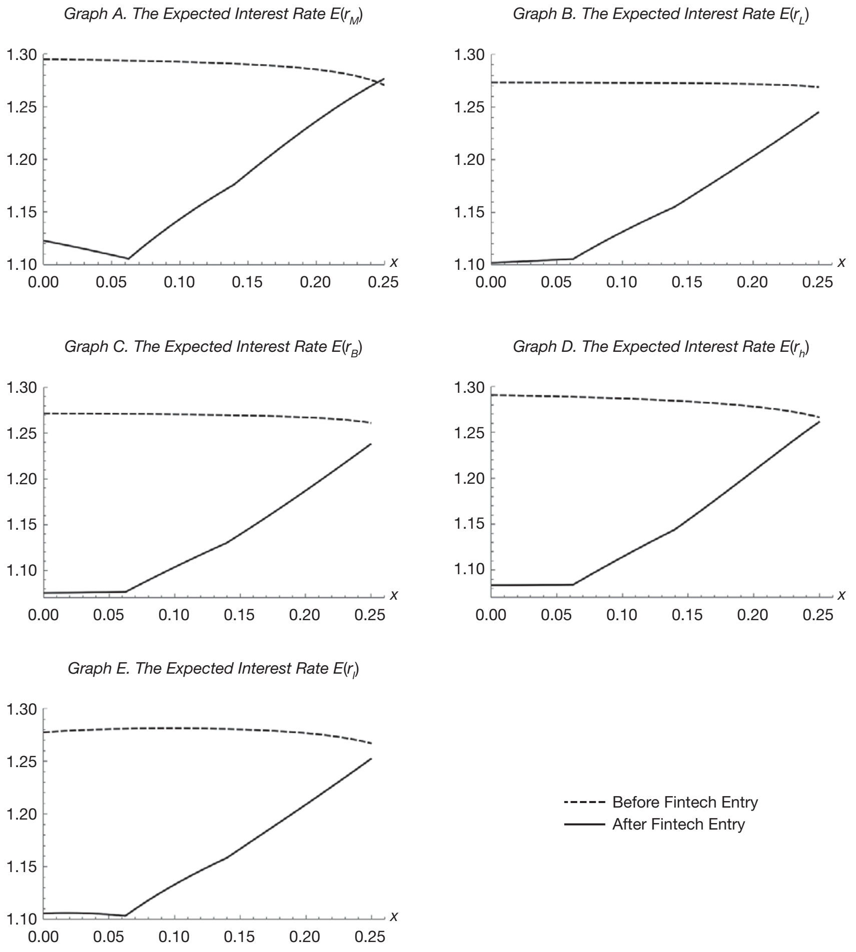
If a borrower's inside bank is more informed than the Fintech lender, the Fintech lender replaces the outside bank as the less informed lender. This change is equivalent to the signal accuracy of the less informed lender increasing from $1/2$ to ϕ_F. However, the Fintech lender offers a lower interest rate than the outside bank as it is better at screening; that is, G_L increases (in the sense of FOSD). The inside bank then lowers its interest rate to compete with the Fintech lender; that is, G_M increases. As an increasing transformation of G_L and G_M, G_B also increases. Therefore, Fintech lending intensifies credit market competition and lowers the expected interest rates.

However, if $\phi_F > \phi(x)$, the effect of Fintech lending on the expected interest rates becomes less straightforward. In this case, the Fintech lender replaces the role of the inside bank as the more informed lender, and the inside bank replaces the role of the outside bank as the less informed lender. While an increase in the less informed lender's screening ability (from $1/2$ to $\phi(x)$) reduces the expected interest rates, an increase in the more informed lender's screening ability (from $\phi(x)$ to ϕ_F) tends to raise the expected interest rates. The change in the expected interest rates is generally ambiguous, so we resort to numerical solutions for a wide range of model parameters. Our numerical exercises show that the Fintech lender's entry decreases the expected interest rates in most cases. However, under certain conditions, a borrower's expected interest rates get higher after the Fintech lender's entry. As an illustration, consider a numerical example with the following parameters:

FIGURE 2

Conditional Expected Interest Rates With and Without the Fintech Lender

In Figure 2, we set the following parameters for all the graphs: $q = 0.8$, $R = 1.3$, $\phi_F = 0.85$, and $\phi(x) = 0.95 - 1.6x$. Graphs A–C, respectively, plot the expected interest rates $E(r_M)$, $E(r_L)$, and $E(r_B)$. Graphs D and E plot the expected interest rates $E(r_h)$ and $E(r_l)$, respectively.



$q = 0.8$, $R = 1.3$, $\phi_F = 0.85$, and $\phi(x) = 0.95 - 1.6x$. Graphs A–C of Figure 2 plot the expected interest rates, $E(r_M)$, $E(r_L)$, and $E(r_B)$, respectively, before and after the Fintech lender's entry. In the region $\phi(x) \geq \phi_F$ ($x \leq 0.0625$), Fintech lending decreases the expected interest rates, $E(r_M)$, $E(r_L)$, and $E(r_B)$, consistent with Proposition 6. In the region $\phi(x) < \phi_F$, both $E(r_L)$ and $E(r_B)$ are lower after the Fintech lender's entry. However, when a borrower's distance to the bank gets sufficiently close to $1/4$, the expected interest rate $E(r_M)$ can become higher with Fintech lending. Intuitively, when the increase in the less informed lender's screening ability is the lowest and the increase in the more informed lender's screening ability is the highest, the interest rate increasing effect is most likely to exceed the interest rate decreasing effect. Nevertheless, the increase in $E(r_M)$ is only possible under very restrictive conditions. This result is similar to that of He et al. (2023), who show that interest rates increase when open banking sufficiently widens the screening ability gap between two lenders and worsens the winner's curse. Graphs D and E plot the expected interest rates of the high- and low-type borrowers, $E(r_h)$ and $E(r_l)$, conditional on receiving at least one offer. Both of them are weighted averages of the expected interest rates $E(r_M)$, $E(r_L)$, and $E(r_B)$.[22] We see that $E(r_h)$ and $E(r_l)$ are lower after the Fintech lender's entry. In the Supplementary Material, we provide more numerical examples to illustrate the effect of Fintech lending on the expected interest rates. Overall, our numerical exercises suggest that Fintech lending reduces the expected interest rates for borrowers in most cases if $\phi_F > \phi(x)$.

E. Fintech Lending and Social Welfare

Finally, we examine whether Fintech lending improves allocative efficiency and social welfare. For borrower x, let $\widehat{w}(x)$ be the expected *net social surplus* resulting from the lending competition between the two incumbent banks without Fintech lending. Then, social welfare $\widehat{W}$ without Fintech lending is measured by the aggregation, i.e., $\widehat{W} = 4\int_0^{1/4} \widehat{w}(x)dx$. Similarly, let $w(x)$ be the expected net social surplus with Fintech lending, and $W = 4\int_0^{1/4} w(x)dx$ measures social welfare.

From a social welfare perspective, it is always desirable to increase the credit availability of high-type borrowers and weed out low-type borrowers. However, by Proposition 5, Fintech lending may either increase or decrease borrowers' access to credit depending on the borrower type and their distance to the inside bank. Therefore, for borrower x, the effect of Fintech lending on the net social surplus is ambiguous. Lemma 2 states the conditions under which the net social surplus increases with Fintech lending.

Lemma 2. Consider a given borrower located at a distance x from its inside bank.

(i) If $\phi_F \leq \left[\frac{qR-1}{1-q} + \frac{1}{\phi(x)}\right]^{-1}$, there exists a $\widehat{R}(x) \in (1/q, r^\star(x))$, where $r^\star(x) = \frac{1}{q} + \frac{1-q}{q}\left(\frac{1}{\phi_F} - \frac{1}{\phi(x)}\right)$, such that the net social surplus increases if and only if $R > \widehat{R}(x)$.

(ii) If $\phi_F > \left[\frac{qR-1}{1-q} + \frac{1}{\phi(x)}\right]^{-1}$, the net social surplus always increases.

The overall effect of Fintech lending sums up the welfare effects across all borrowers in the circle. The main results are presented as follows.

Proposition 7. (i) There exists a $R \in \left(\frac{1}{q}, \frac{1}{q} + \frac{1-q}{q}\left(\frac{1}{\phi_F} - \frac{1}{\phi(0)}\right)\right)$ such that it is socially efficient for the Fintech lender to enter the market, i.e., $\widehat{W} > W$, if $R > \widehat{R}$.

(ii) If $R > 1/q$ is sufficiently small and ϕ_F is sufficiently small, then it is socially inefficient for the Fintech lender to enter the market, i.e., $\widehat{W} \leq W$.

Proof. In the Supplementary Material.

[22]Note that $E(r_t) = \Pr(M|t)E(r_M) + \Pr(L|t)E(r_L) + \Pr(B|t)E(r_B)$, $t \in \{h, l\}$, where $\Pr(M|t)$, $\Pr(L|t)$, and $\Pr(B|t)$, respectively, are the probabilities of a borrower's loan application being accepted by the more informed lender only, by the less informed lender only, and by both lenders conditional on the borrower type t.

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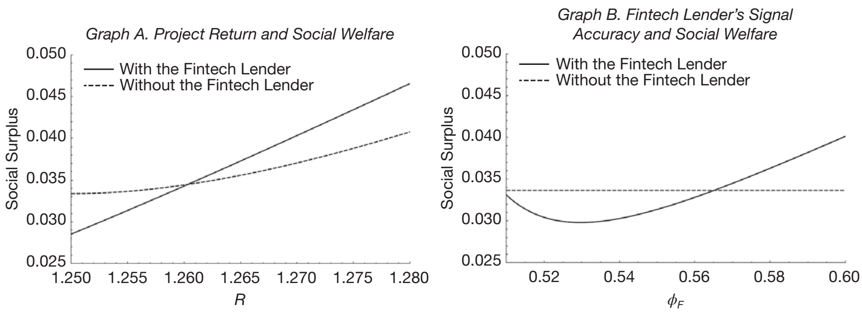
FIGURE 3

Social Surplus With and Without the Fintech Lender

In Figure 3, we set the following common parameters for two graphs: $q = 0.8$ and $\phi(x) = 0.9 - 0.4x^{0.1}$. Graph A plots the relationship between social surplus and the borrower's return conditional on success R in a market with and without the Fintech lender, respectively, given $\phi_F = 0.55$. Graph B plots the relationship between social surplus and the Fintech lender's signal accuracy ϕ_F in a market with and without the Fintech lender, respectively, given $R = 1.255$.



Proposition 7 shows that Fintech lending improves social welfare when project return R is sufficiently high. In this case, the benefit of financing high-type borrowers is large. For most high-type borrowers in the circle, Fintech lending increases their access to credit; thus, social welfare is improved. However, when two conditions hold, social welfare may decrease with Fintech lending: one condition is that the project return R is sufficiently small, and the other is that the Fintech lender's signal accuracy ϕ_F is sufficiently small. In this case, upon the entry of the Fintech lender, the credit availability for a large number of low-type borrowers increases. The magnitude of the expected welfare loss from financing low-type borrowers increases more than the expected gain from financing high-type borrowers. To see this more clearly, consider a numerical example, in which we set $q = 0.8$, $R = 1.255$, $\phi_F = 0.55$, and $\phi(x) = 0.9 - 0.4x^{0.1}$. In this example, social surplus decreases by approximately 7% (from 0.0337 to 0.0314) after the Fintech lender's entry.

Graph A of Figure 3 illustrates social welfare as a function of the borrower's return conditional on success R in the market with and without the Fintech lender, respectively. In either scenario, social surplus increases with return R. However, the curve has a steeper slope in the market with the Fintech lender than in the market without it. When R is small, the market's social surplus with the Fintech lender is smaller than in the market without it. As R increases, the social surplus increases more in the market with the Fintech lender than in the market without it. At some point, social surplus in the market with the Fintech lender surpasses that of the market without it. However, we note that the welfare-reduction effect of Fintech lending may not be a problem if its entry or screening is sufficiently costly. As illustrated, Fintech lending reduces overall social surplus if both the project return is low and the Fintech lender's information quality is poor. These conditions imply low profits for the Fintech lender, which would be reluctant to enter the market if the costs of entry or operation are sufficiently high.

F. Empirical Implications

Our model has numerous empirical predictions. First, it predicts that the Fintech lender's entry crowds out banks that specialize in transactional lending.[23] This is consistent with the empirical evidence in Balyuk et al. (2020), who find that Fintech lending tends to replace loans by large and out-of-market banks.[24] Second, the model predicts that banks' profits decrease after the Fintech lender's entry and that the decreases are greater in regions further from the banks, in line with the empirical findings in Cornaggia et al. (2019). Third, our analysis predicts that Fintech lending unambiguously increases the credit availability of high-type borrowers if they are close to the inside banks. Such borrowers are banks' major clients, and so our prediction matches the empirical observations of Tang (2019), who finds that borrowers who already have access to bank credit are the most likely to benefit from credit expansion due to Fintech lending. Finally, the model suggests that in places where Fintech lenders have better information than banks, they can charge higher interest rates and earn higher profits. This implies that the rate differential between Fintech lenders and traditional banks is the largest for borrowers with a short credit history, which is consistent with the findings of Di Maggio and Yao (2021). Moreover, Di Maggio, Ratnadiwakara, and Carmichael (2022) show that lending to borrowers with a thin credit history leads to higher returns for the Fintech lender.

Our analysis also offers new predictions that are untested in the empirical literature. First, banks' approval rates of loan applications decline after the Fintech lender's entry, especially for "distant" borrowers with a short credit history. Second, the cost of bank credit decreases for borrowers close to banks. Third, as the Fintech lender obtains more borrower data and improves its credit scoring ability, it will charge higher interest rates for borrowers with a thin credit history.

V. Conclusion

The rise of Fintech lending has received much attention from academics and policymakers. This article considers a stylized lending competition model, with two incumbent banks and one potential entrant (a Fintech lender) to study the effect of Fintech lending. In the model, the incumbent banks and Fintech lender screen and compete for borrowers and their signals of borrowers' creditworthiness are conditionally independent and asymmetric.

We first solve a lending competition game between two asymmetrically informed lenders with independent signals. A unique mixed-strategy equilibrium exists in such a game, which crucially depends on the screening ability gap between the two lenders. When the screening ability gap is small, both lenders accept loan applications with a good signal. However, when the screening ability gap is large,

[23]Following Hauswald and Marquez (2006), we can interpret the loans provided by the outside bank as transactional loans and the loans provided by the inside bank as relationship loans.

[24]See, e.g., Berger and Udell (2002) and Berger, Miller, Petersen, Rajan, and Stein (2005) for empirical evidence on the different lending technologies of large and small banks. A common finding in this line of work is that large banks rely more on transactions-based lending technologies, whereas small banks specialize in relationship lending because they are better at collecting soft information.

the less informed lender sometimes rejects borrowers with a good signal. Based on this result, we characterize the three-lender competition equilibrium with Fintech lending.

We show that for a given borrower, Fintech lending crowds out the outside bank and competes directly with the inside bank. Although Fintech lending provides borrowers with more options for obtaining credit, it also leads to adverse selection for the existing banks and decreases their credit supply. Therefore, Fintech lending may not necessarily benefit borrowers with observably poor but actually good credit quality. Furthermore, we find that Fintech lending unambiguously reduces the expected interest rates for borrowers close to their inside bank. When the borrowers' project return and the Fintech lender's signal accuracy are low, the Fintech lender's entry is detrimental to allocative efficiency as it would finance too many low-type borrowers.

There are some issues that we leave for future research. First, in addition to the screening technologies used, there can be other differences between Fintech lenders and traditional banks, such as convenience and trust. It would be interesting to incorporate some of these elements into the model; however, we believe that this would not change our main results substantially. Second, we focus on the competition between banks and the Fintech lender. However, the relationship between banks and Fintech lenders can also be complementary or cooperative in credit provision. It would be interesting to explore the optimal form of cooperation between the two types of lender.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000698.

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