Open Banking: Credit Market Competition When Borrowers Own the Data*

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Abstract

Open banking facilitates data sharing consented to by customers who generate the data, with a regulatory goal of promoting competition between traditional banks and challenger fintech entrants. We study lending market competition when sharing banks' customer transaction data enables better borrower screening. Open banking could make the entire financial industry better off yet leave all borrowers worse off, even if borrowers could choose whether to share their data. We highlight the importance of the equilibrium credit quality inference from borrowers' endogenous sign-up decisions, and study extensions with fintech affinities and data sharing on borrower preferences.

Keywords: Open banking, Data sharing, Banking competition, Digital economy, Winner's curse, Privacy, Loan targeting

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

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1 Introduction

The world is racing toward an era of open-data economy, thanks to rapidly evolving information and digital technology. Customer data—instead of being zealously guarded and isolated within individual organizations or institutions—have become more "open" to external third parties, whenever customers who generate these data consent to share them.

Open banking, an initiative launched by several governments including the European Union and the U.K., leads such a shift toward the open-data economy guided by the General Data Protection Regulation (GDPR). Importantly, the core principle of open banking does not stop at "customer ownership" of their own data. Aiming at "customer control," the Second Payment Services Directive (PSD2) envisions enabling customers to voluntarily share their financial data with other entities, via application programming interfaces (APIs). Indeed, PSD2, by mandating European banks embrace the API technology, explicitly empowers customers with the authority to share their banking data, removing the financial institution's role as gatekeeper.[1] As the global discussion unfolds, many practitioners and policy makers expect open banking, which "is disruptive, global and growing at a breakneck pace" according to Forbes,[2] to represent a transformative trend in the banking industry in the coming decade.

When Deloitte Insight conducted a survey on open banking in April 2019, it employed the following "descriptive" definition of open banking, which vividly captures its essence:[3]

> Imagine you want to use a financial product offered by an organization other than your bank. This product could be anything you feel would help you, such as an app that gives you a full picture of your financial status, including expenses, savings, and investments or it could be a mortgage or line of credit. But for this product to be fully useful to you, it needs information from your bank, such as the amount of money you have coming in and going out of your accounts, how many accounts you have, how you spend your money, how much interest you

[1]The PSD2 in European Union mandates European banks create best practices in APIs, vendor integration, and data management. Loosely speaking, application programming interfaces (APIs) allow users to synchronize, link, and connect databases; in the context of a banking system, they link a bank's database (its customers' information) with different applications or programs, thus forming a network encouraging the promotion of services, payments, and products appropriate to each person. For more information on APIs, see Appendix B.

[2]See the two-part series (one and two) "Open Banking Is Now Essential Banking: A New Decade's Global Pressures And Best Responses" by Forbes in early 2021.

[3]See endnote 1 on page 17 in Srinivas, Schoeps, and Jain (2019) at `https://bit.ly/3mIdm2N`.

> have earned or paid, etc. You then instruct your bank to share this information with this other institution or app. Should you wish to stop using this product, you can instruct your bank to stop sharing your data at any given point in time, with no strings attached. This concept is called *open banking*.

Open banking is no longer only a European initiative. In the U.S., for decades traditional banks have used credit reports as the main tools to determine who gets a loan. However, credit reports generally reflect a person's borrowing history, leaving customers with only cash or debit cards unserved. In 2019, FICO, Experian, and Finicity jointly launched a pilot program called "UltraFICO" through which borrowers can *choose* to share their bank account information with lenders in addition to their traditional FICO scores.[4] And, a recent WSJ article reports that JPMorgan, Bank of America and other big banks have been using their own customers' bank-account activity to approve financing for applicants with limited credit histories. A natural question is: why can't JPMorgan approve a credit-card application from a borrower who has a deposit account at Wells Fargo, if this borrower agrees? Indeed, this WSJ article reported that "*About 10 banks agreed to exchange data, (which is) an unusual level of collaboration*." This is essentially open banking.[5]

We provide a brief overview of open banking in Appendix B, with the theme of credit market development and competition given the focus of paper. Borrowers' information sharing—especially their bank account data—is instrumental for fintech firms (say, LendingClub in the U.S. or MarketPlace in the U.K.) who specialize in small business and consumer lending. Dan Kettle at Pheabs, a U.S. fintech company, argues that

> Open banking is certainly revolutionary when it comes to underwriting loans. Previously, we would run hundreds of automated rules and decisions to determine which customer was best to lend to ... (but) these could never be fully verified and you were still taking on some level of risk. But with open banking, we now see the exact bank transactions that customers have had over the last few weeks and months. In particular, if there is a history of repeat gambling or taking out

[4]For more details, see link and discussion in Section 3.1. And, as a part of effort to bolster its open banking, Equifax has acquired AccountScore to enhance its consumer and commercial product offerings, combining traditional credit bureau information held by Equifax with bank transaction data, facilitated by AccountScore. According to the website of Equifax, integration of these new data assets will not only benefit lenders from higher rates of automated, digital income verification, but also promote financial inclusion for those with "thin" credit files.

[5]This plans grew out of Project REACh (Roundtable for Economic Access and Change), now an effort launched by the Office of the Comptroller of the Currency. For details, see this WSJ report.

> other high cost loans ... (then) we should be more cautious with this kind of client—maybe declining them or charging a higher rate.

The idea to let borrowers decide if they want to share data with some third parties—especially competing fintech lenders—has profound implications on credit market competition and welfare. Although the role of information technology has been extensively studied in the banking literature, our paper emphasizes that, unlike traditional practice where lenders acquire borrowers' credit reports, under open banking it is borrowers who control lenders' access to borrower information via their own data sharing decisions. This conceptual difference is the cornerstone of our analysis, and begets many important questions regarding the welfare implications of open banking.

Our model, following Broecker (1990) and Hauswald and Marquez (2003), considers a traditional bank and a fintech lender who conduct independent but imperfect creditworthiness tests before making loan offers to borrowers. Each borrower can have either high or low credit quality, and the test yields a binary signal of their credit quality. Similar to common-value auctions, an important feature of this market is a winner's curse (i.e., winning a borrower implies the possibility that the rival lender has observed an unfavorable signal of the borrower's credit quality). This winner's curse essentially determines the lending cost. In equilibrium, the lender with a stronger screening ability faces a less severe winner's curse and earns a positive profit, while the other weaker lender earns a zero profit and sometimes declines to extend an offer even upon seeing a favorable signal.

We use this baseline credit market competition framework to study the impact of open banking. Traditional banks enjoy a great advantage from the vast amount of customer data they possess (say, from transaction accounts, direct deposit activities, etc). Fintech lenders are often equipped with limited data (usually restricted to social activities and profiles); however, they have developed much more advanced data analysis algorithms, though without enough data a better algorithm does not yield more useful information. Therefore, in our benchmark case with no open banking, we assume that the bank has a better screening ability than the fintech lender. (We define screening ability as the joint outcome of data availability and data analysis techniques.)

Open banking, by allowing borrowers to share their bank data, can greatly enhance the competitiveness of the fintech lender as a "challenger." Once the fintech has access to the bank's data, we assume that its screening ability is improved. Because the fintech has a more advanced data analysis algorithm, it could even surpass the bank in screening borrowers, especially when it also has some independent data sources.[6] The improvement of the fintech's screening ability has two effects: a standard "information effect" that helps high credit quality borrowers but hurts low credit quality borrowers, and a "strategic effect" that affects the degree of lending competition. This "strategic effect" can go in either direction: lending competition will be intensified (softened) if the screening ability gap between the two lenders shrinks (expands). In particular, if open banking expands the screening ability gap sufficiently (i.e., if open banking "over-empowers" the fintech), it will hurt both types of borrowers but improve industry profit. Reflecting on the celebrated selling point that open banking promotes competition and benefits borrowers, we hence highlight that data sharing may backfire and increase the competitiveness of the challenger lender too much.

We then ask: can the very nature of open banking—borrowers deciding whether to opt in to share their banking data with the fintech lender—prevent this perverse effect of open banking on borrowers? After all, borrowers ought not to act against their own interest. Our analysis with voluntary sign-up decisions provides a negative answer to this question. We show that when the fintech becomes sufficiently strong (stronger than the bank), then in the unique nontrivial equilibrium,[7] high-type borrowers opt in while some low-type borrowers opt out, and all borrowers can get strictly worse off than before open banking. Those who sign up suffer due to weakened competition as a result of the enlarged lender asymmetry caused by data sharing, while those who do not sign up suffer due to an adverse equilibrium inference that opting-out signals poor credit quality.

Our theory thus highlights a potential perverse effect of open banking in which all borrowers might be hurt even with voluntary sign-ups. In practice, while incumbents still hold the keys to the vault in terms of rich transaction data, banks often view the opening of these data flows as more of a threat than an opportunity. This is especially true in regard to fintech challengers who have gained valuable digital customer relationships and are equipped with better data analysis technology; in exactly this situation, the perverse effect of open banking is more likely to arise. The adverse credit quality inference of opting-out, which is driven by the very fact that high-type borrowers have more incentive to share their credit data with lenders, is the key to this potential perverse effect.

We consider several extensions and provide related discussions in Section 4. The presence

[6]For example, Berg, Burg, Gombović, and Puri (2020) provide evidence that fintech lenders use a different source of information, digital footprints, to assess customers' creditworthiness; digital footprints improve the predictive power of traditional credit bureau data when combined with the latter.

[7]There always exists a "trivial" equilibrium where nobody signs up for open banking, in which open banking has no impact on the market outcome.

of multiple fintech lenders, if they survive in equilibrium after open banking (which is a significant "if" due to the celebrated winner's curse effect), will in general intensify the competition after open banking and hence alleviate the perverse effect identified in this paper. However, borrowers' affinities toward fintech loans make the perverse effect of open banking more likely to occur: By granting the fintech lender local market power, fintech affinity complements the fintech lender's screening ability boosted by open banking and weakens the competition further. Finally, we show that perverse effect also exists if open banking involves data sharing on customer preferences. Overall, this section helps illustrate the generality of the perverse effect given the endogenous credit quality inference: even without a fintech that is much stronger than the incumbent bank after open banking, all customers could be hurt.

In sum, by conducting a normative analysis within a canonical economic framework, our paper explores the welfare implication of open banking with informed consent when sharing data on credit quality or costumer preference. Though the ensuing disruption to the banking industry could bring significant benefit to challenger fintechs as well as customers, our analysis highlights a perverse effect of open banking and calls further study to better understand the implications of "sharing" in an open data economy.

Related Literature

Lending market competition with asymmetric information. Our paper is built on Broecker (1990), who studies lending market competition with screening tests. In Broecker (1990), banks are *symmetric* and possess the same screening ability, while both our paper and Hauswald and Marquez (2003) consider asymmetric screening abilities.[8] Hauswald and Marquez (2003) study the competition between an inside bank that can conduct credit screening and an outside bank that has no access to screening. They consider the possibility of information spillover to the outside bank, which reduces the inside bank's information advantage and benefits borrowers.

Our paper differs from Hauswald and Marquez (2003) in three important aspects: First, in our model, open banking can empower the fintech (the initial weak lender) so that it exceeds the traditional bank in screening ability, which can harm all borrowers. Second, an important feature of open banking, which we highlight in this paper, is that customers have

[8]Lending market competition with asymmetric screening abilities is related to common-value auctions with asymmetrically informed bidders. Hausch (1987), Kagel and Levin (1999), and Banerjee (2005) explore information structures that allow each bidder to have some private information (which is the information structure adopted in Broecker (1990) and our paper).

control over whether to share their data, and their sign-up decision itself can potentially reveal further creditworthiness information. Third, open banking can also reveal noncredit privacy information to the fintech lender. How this enables the fintech to make more targeted loan offers and affects lending market competition has not been investigated in the literature.

Asymmetric credit market competition can also arise from the bank-customer relationship, as a bank knows its existing customers better than a new competitor does; this idea was explored by Sharpe (1990).[9] In our model, information asymmetry before open banking exists for the same reason: traditional banks own the customer data that fintech lenders cannot access, so that even if fintech lenders have a better data processing algorithm, they screen borrowers less accurately.

Our paper is also related to the literature on credit information sharing among banks; e.g., Pagano and Jappelli (1993) and Bouckaert and Degryse (2006).[10] More broadly, lending market competition with asymmetric information is important for studying many issues such as capital requirements (e.g., Thakor, 1996), borrowers' incentives to improve project quality (e.g., Rajan, 1992), information dispersion and relationship building (e.g., Marquez, 2002), credit allocation (e.g., Dell'Ariccia and Marquez, 2004, 2006).

Fintechs. Our paper connects to the growing literature on fintech disruption (see, for instance, Vives, 2019; Berg, Fuster, and Puri, 2021, for a review of digital disruption in banking), in particular on fintech companies competing with traditional banks in originating loans (e.g., Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Tang, 2019).[11] Berg, Burg, Gombović, and Puri (2020) find that even simple

[9]In the two-period model analyzed in Sharpe (1990), asymmetric competition arises in the second period (with the corrected analysis of a mixed-strategy equilibrium offered by Von Thadden (2004)). Recently, Yannelis and Zhang (2021) show that increased lender competition can hurt consumer welfare in subprime credit markets, in a similar vein to the perverse effect of open banking in our paper. The lenders' endogenous information acquisition plays a key role in their paper, while our study focuses on the equilibrium inference of borrowers' decision in sharing their own data.

[10]These two papers differ from ours in terms of focus as well as framework. Pagano and Jappelli (1993) study a collective decision on information sharing among banks (e.g., by setting up a credit bureau) where each bank acts as a monopolist in a local market. A bank can tell its residential borrowers' types and so offers type-dependent deals, but it does not know the types of borrowers who immigrate from other markets and so has to offer them a uniform interest rate. Once customer information is shared, each bank can discriminate over different types of immigrant borrowers as well. Bouckaert and Degryse (2006) study banks' individual incentives to share customer information. They argue that an incumbent bank has a strategic incentive to share partial customer information to reduce the entry of new competitors. In our paper, the sharing of bank customer data to the fintech is facilitated by open banking regulation and importantly is controlled by customers themselves.

[11]Blockchain and its underlying distributed ledger technology are another important disruption force in today's financial industry that has received great attention since the launch of Bitcoin. For related work on this topic, see Biais, Bisière, Bouvard, and Casamatta (2019); Cong and He (2019) and Abadi and

digital footprints are informative in predicting consumer default, as a complementary source of information to traditional credit bureau scores. Di Maggio and Yao (2020) find that fintech lenders serve borrowers of decent credit quality by financing higher consumption expenditures, who then default ex post more frequently than similar borrowers with nonfintech lenders. Their paper suggests a story in which some borrowers' desire for immediate consumption with fintech loans exacerbates their self-control issues to overborrow, a point that is consistent with one interpretation of the captured customers that we study in Section 4.3.

On the theoretical font, Parlour, Rajan, and Zhu (2020) is closely related to our work by studying a bank that operates in both payment service and credit (loan) markets; the vertically integrated bank competes with stand-alone fintechs on payment services as well as stand-alone fintech lenders. Parlour, Rajan, and Zhu (2020) stress that customers' payment services provide information about their credit quality, and this payment-service information is equally useful for two lenders in their paper. In contrast, in our model this payment-service information can improve the two lenders' screening technologies differently, given their different data analysis algorithms. This heterogeneous information effect drives our non-trivial welfare result.[12]

Consumer privacy. Our paper also contributes to the burgeoning literature on consumer privacy (see, for instance, Acquisti, Taylor, and Wagman, 2016; Bergemann and Bonatti, 2019, for recent surveys), and is particularly related to work on the impact of letting consumers control their own data.[13] Aridor, Che, and Salz (2020) offer evidence that the equilibrium "inference" on customers is well founded, by showing that letting privacy-conscious consumers opt out of data sharing under GDPR increases the average value of the remaining consumers to advertisers.

2 The Baseline Model

This section introduces the basic model of credit market competition that will be used as a building block in later sections when we study open banking. Table 1 in Appendix A.1

Brunnermeier (Working Papers).

[12]In their base model, there is no equilibrium credit quality inference (which plays the key role in our analysis), because whether a consumer switches to a fintech payment service is driven by her bank-affinity preference, which is independent of her credit quality type. The equilibrium credit quality inference occurs in their model extension when consumers can port data after the consumer observes her credit quality; there, the standard unraveling mechanism in Milgrom (1981) implies that everyone shares the data in equilibrium.

[13]Recent research (e.g., Ichihashi, 2020; Liu, Sockin, and Xiong, 2020; Jones and Tonetti, 2020) suggests that the market equilibrium consequence of consumer privacy choices is highly context dependent.

provides lists of the notation used in this paper. All proofs are given in the Appendix.

2.1 Borrowers

There is a continuum of risk-neutral borrowers of measure 1. Each is looking for a loan of size 1. Borrowers differ in their default risk: a fraction $\theta \in (0, 1)$ of them are high-type (h) borrowers who, for simplicity, are assumed to always repay their loans, and the rest $1 - \theta$ of them are low-type (l), who always default and repay nothing. Each borrower's type is that borrower's private information, but the type distribution is publicly known. Let

$$\tau \equiv \frac{\theta}{1-\theta}$$

be the likelihood ratio of high-type over low-type borrowers in the population, which represents the average credit quality of borrowers (as reflected by all public information, for instance their credit scores). We will discuss the important difference between open banking and traditional credit reports in Section 3.1 when we formally introduce open banking in our model.

We assume that the interest rate in the market never exceeds $\bar{r}$. There are at least two interpretations of this assumption. Borrowers can be small business firms, each having a project in which to invest but differing in the probability that their project will succeed. When the project succeeds, it yields a net return $\bar{r}$, which is observable and contractible; when it fails, it yields nothing. Protected by limited liability, borrowers will never pay an interest rate above $\bar{r}$. Alternatively, borrowers can be ordinary consumers who need a loan to purchase a product but differ in the probability that they will be able to repay the loan. (For instance, a consumer will default if she becomes unemployed, and consumers face different unemployment risks.) In this case, the interest rate is capped at $\bar{r}$ either due to interest rate regulation (e.g., usury laws, which cap the rate by 36% in many jurisdictions),[14] or because of some exogenous outside options. We assume that the utility from consuming the product is sufficiently high that borrowers are willing to borrow at $\bar{r}$.[15]

[14] Usury laws prohibit lenders from charging borrowers excessively high interest rates on loans. In the U.S., many states have established caps on the interest rate that lenders can charge for small dollar loans, such as payday and auto-title products. See, for instance, https://bit.ly/3mhJn2b for details.

[15] In this case, for a borrower of type $i \in \{h, l\}$, denote by $u_i > 0$ the utility from consuming the product. Then the low types are of course willing to borrow since they never repay the loan. We assume that $u_h - (1 + \bar{r}) \geq 0$ so that the high-type consumers are willing to borrow at interest rate $\bar{r}$. Also see related discussions toward the end of Section 2.2.

2.2 Lenders and Screening Ability

There are two risk-neutral competing lenders in the market. When a borrower applies for a loan, each lender conducts an independent creditworthiness test before deciding whether to make an offer. We are interested in the case when one lender has a better screening ability than the other. As we emphasized in the introduction, screening ability includes both data availability and the data processing technique/algorithm. We call one of the lenders a strong lender (denoted by s) and the other a weak lender (denoted by w). When it comes to the open banking applications in next sections, the two lenders will be a traditional bank and a fintech lender. We consider the case with more than one fintech lender in Section 4.1.

Following Broecker (1990), we assume that each lender receives an independent and private signal of a borrower's type via credit screening. Let $S_j \in \{H, L\}$ denote lender j's signal, where $j \in \{s, w\}$. For simplicity, we assume that when a borrower is of high type, each lender is certain to observe a high signal H for sure; when a borrower is of low type, the signal is noisy:

$$\mathbb{P}\left(S_s = L \,|\, l\right) = x_s > \mathbb{P}\left(S_w = L \,|\, l\right) = x_w,$$

i.e., the strong lender is better at detecting low types than the weak lender, and thus has a better screening ability. The two lenders' screening abilities are publicly known. Notice that we have a "bad-news" signal structure, i.e., a bad signal perfectly reveals a borrower to be of low type while a good signal is inconclusive. In the following, we use high (low) signals and good (bad) signals interchangeably.

For our exercise, the winner's curse as one of the key mechanisms could be delivered by other types of information structures, but the bad-news structure greatly helps with tractability. This structure is also consistent with the empirical pattern of fintechs promoting financial inclusion by serving subprime borrowers; these underserved subprime borrowers have lower average quality as characterized by a small τ, and fintechs can screen out some high-type borrowers (independent of the bank's screening).[16]

After receiving private signals, lenders update their beliefs about the borrower's type and make their loan offers $r_j \in [0, \bar{r}]$ (if any) simultaneously. The borrower chooses the offer with the lower interest rate.[17] (When the two lenders offer the same deal, the borrower randomly picks one offer, though the details of the tie-breaking rule do not affect our analysis.) For

[16] For different information structures, see Chu and Wei (2021), Hau, Huang, Shan, and Sheng (2019) and others.

[17] Although low-type borrowers always default, we assume that they prefer a cheaper loan, which can be justified if their repayment probability is slightly above zero.

simplicity, we assume that the two lenders have the same funding costs which we normalize to 1.[18]

In our setting, no lender will make loan offers to a borrower upon seeing a low signal. We assume that each lender is willing to lend to a borrower with a high signal H at the highest possible interest rate $\overline{r}$. The details of this assumption are as follows. For lender j, the chance to observe a high signal from a borrower is $\theta + (1-\theta)(1-x_j)$. Upon seeing a high signal, it expects a repayment rate of

$$\frac{\theta}{\theta + (1-\theta)(1-x_j)} = \frac{\tau}{\tau + 1 - x_j},$$

where recall $\tau = \frac{\theta}{1-\theta}$. The lender is willing to lend at $r = \overline{r}$ if this expected repayment rate times $1 + \overline{r}$ exceeds the cost 1. This requires

$$\tau\overline{r} > 1 - x_j. \tag{1}$$

As the only mistake lenders may make is lending to a low-type borrower (due to the bad-news signal structure), this condition holds more easily when there are more high-type borrowers in the population, i.e., a higher τ, or when the screening ability is better.

Finally, we assume that any borrower of type i obtains a non-monetary benefit δ_i just from getting a loan. As high-type borrowers always enjoy δ_h and it plays no role in our subsequent analyses, we normalize δ_h to 0 for convenience. We, however, set $\delta_l = \delta > 0$, which can be interpreted as the control rent of entrepreneurs from nonpledgeable income (see, for instance, Tirole, 2010) in the context of small business loans, or consumption utility in the context of consumer loans. This implies that low-type borrowers who never succeed still care about the likelihood of getting a loan, rendering a meaningful analysis of the low-type borrowers' welfare. For our applications we think about δ as relatively small,[19] though this assumption plays little role as our welfare analysis focuses on the Pareto criterion for consumers without transfer.

[18] We could alternatively assume that the fintech lender has a higher financing cost, which is a well-known empirical regularity due to fintechs' lack of cheap and stable funding sources like deposits. However, considering asymmetric funding costs would only complicate the analysis without adding significant economic insights given our focus.

[19] Specifically $0 < \delta < 1$, and the low types should not receive a loan from the perspective of the social planner. Hence in our paper, financial inclusion itself is not socially beneficial.

2.3 Equilibrium Characterization

We now characterize the unique (mixed-strategy) equilibrium for credit market competition.

2.3.1 Preliminary analysis

Let

$$p_{HH} \equiv \mathbb{P}(S_s = H, S_w = H) = \theta + (1-\theta)(1-x_s)(1-x_w)$$

be the probability that both lenders observe a good signal from a borrower, and let

$$\mu_{HH} \equiv \frac{\theta}{p_{HH}}$$

be the probability of repayment of a borrower conditional on that. Similarly, denote by

$$p_{HL} \equiv \mathbb{P}(S_s = H, S_w = L) = (1-\theta)(1-x_s)\,x_w$$

the probability that the strong lender observes a good signal but the weak lender observes a bad signal, and by

$$p_{LH} \equiv \mathbb{P}(S_s = L, S_w = H) = (1-\theta)\,x_s(1-x_w)$$

the probability of the opposite event. In either case, the expected repayment probability is zero. Note that $p_{LH} > p_{HL}$ given that $x_s > x_w$.

The credit market competition in our model has the flavor of common-value auctions. A lender wins a borrower if it offers a lower interest rate than its rival, or if the rival rejects the borrower after seeing a bad signal. In the latter case, the lender suffers due to the winner's curse by serving a low-type borrower. As a common result in the literature (see Broecker, 1990), there is no pure-strategy equilibrium due to winner's curse.[20]

We introduce some notation to characterize the mixed-strategy equilibrium that arises.

[20] In any pure strategy equilibrium, it is impossible that the two lenders offer different interest rates; otherwise the lender offering a lower interest rate could always raise its interest rate slightly without losing any demand. If they charge the same interest rate r and make a nonnegative profit, which is

$$p_{HH} \times \underbrace{\frac{1}{2}}_{\text{tie-breaking}} [\mu_{HH}(1+r) - 1] - \underbrace{p_{HL}}_{\text{winner's curse}}, \tag{2}$$

then the first portion in (2) must be strictly positive, in which case each lender will have a unilateral incentive to undercut its opponent. The mixed-strategy equilibrium behaves well as shown in Online Appendix C.1.

Let m_j, $j \in \{s, w\}$, be the probability that lender j makes an offer to a borrower upon seeing a good signal. (As we will see, in the mixed-strategy equilibrium, the strong lender will always make an offer after seeing a good signal, while the weak lender will sometimes not make an offer.) Let $F_j(r) \equiv \Pr(r_j \leq r)$ be lender j's interest rate distribution conditional on making an offer; it can be shown that the two lenders' distributions must share the same support with a lower bound $\underline{r}$ (which will be specified below) and an upper bound $\overline{r}$. For our subsequent analysis, it is more convenient to use the survival function $\overline{F}_j(r) \equiv 1 - F_j(r)$. Let π_j be the lender j's equilibrium (expected) profit.

In a mixed-strategy equilibrium, the strong lender's indifference condition is

$$p_{HH}\left[1 - m_w + m_w \overline{F}_w(r)\right]\left[\mu_{HH}(1+r) - 1\right] - p_{HL} = \pi_s. \tag{3}$$

When the strong lender offers interest rate r upon seeing a good signal, there are two possibilities: first, if the weak lender also observes a good signal (which occurs with probability p_{HH}, then the strong lender wins both when the the weak one does not make an offer (which occurs with probability $1 - m_w$ and when the weak one makes an offer at above r (which occurs with probability $m_w \overline{F}_w(r)$); second, if the weak lender observes a bad signal instead (which occurs with probability p_{HL}) and hence makes no offer, the borrower must be of low type and so the strong lender makes a loss of 1. Similarly, the weak lender's indifference condition is

$$p_{HH}\left[1 - m_s + m_s \overline{F}_s(r)\right]\left[\mu_{HH}(1+r) - 1\right] - p_{LH} = \pi_w. \tag{4}$$

Lemma 1. *In any mixed-strategy equilibrium, the strong lender makes a strictly positive profit $\pi_s > 0$ while the weak lender makes a zero profit $\pi_w = 0$.*

This is because the weak lender faces a higher lending cost due to its more severe winner's curse (i.e., $p_{LH} > p_{HL}$). Given that there is no product differentiation, only the lender with the lower cost makes a positive profit. As we will see below, the strong lender's profit equals $p_{LH} - p_{HL} = (1-\theta)(x_s - x_w)$.

2.3.2 Mixed-strategy competition equilibrium

Now we fully characterize the mixed-strategy equilibrium with $\pi_s > \pi_w = 0$. The strong lender must always make an offer upon seeing a good signal (i.e., $m_s = 1$) because of its strictly positive profit. Equation (4) then simplifies to

$$p_{HH}\overline{F}_s(r)\left[\mu_{HH}(1+r) - 1\right] - p_{LH} = 0. \tag{5}$$

To make this equation hold for r close to $\overline{r}$, we need F_s to have a mass point at the top. Let $\lambda_s \equiv \lim_{r\uparrow\overline{r}} \overline{F}_j(r) \in [0,1)$ be the size of the mass point. (This also implies that the support of F_w must be open at the top.) From (3) and (5), we can uniquely solve for all four endogenous variables $(\underline{r}, \pi_s, m_w, \lambda_s)$ and the two distributions. For notational convenience, we define

$$\phi(r) \equiv \frac{p_{LH}}{p_{HH}\left[\mu_{HH}(1+r)-1\right]} = \frac{x_s}{\frac{\tau}{1-x_w}r - 1 + x_s}, \tag{6}$$

which is $\overline{F}_s(r)$ solving (5). Note that $\phi(r)$ depends on primitive parameters x_w, x_s, and τ, and Assumption (1) implies that $\phi(\overline{r}) \in (0,1)$. Denote by Δ the gap in screening ability between the two lenders:

$$\Delta \equiv x_s - x_w.$$

Then the mixed-strategy equilibrium is characterized as follows:[21]

Proposition 1. *The competition between the two lenders has a unique equilibrium in which*

1. *the strong lender makes a profit* $\pi_s = \frac{\Delta}{1+\tau}$ *and the weak lender makes a zero profit* $\pi_w = 0$*;*

2. *the strong lender always makes an offer upon seeing a high signal* ($m_s = 1$)*, and its interest rate is randomly drawn from the distribution* $\overline{F}_s(r) = \phi(r)$*, which has support* $[\underline{r}, \overline{r}]$ *with* $\underline{r} = \frac{1-x_w}{\tau}$ *and has a mass point of size* $\lambda_s = \phi(\overline{r})$ *at* $\overline{r}$*; and*

3. *the weak lender makes an offer with probability* $m_w = 1-\phi(\overline{r})$ *upon seeing a high signal, and when it makes an offer, the interest rate is randomly drawn from the distribution*

$$\overline{F}_w(r) = \frac{\phi(r) - \phi(\overline{r})}{1-\phi(\overline{r})},$$

which has support $[\underline{r}, \overline{r})$*.*

[21] It is worth noting that Proposition 1 applies to the (generic) case of $x_s > x_w$ only; the edge case $x_s = x_w$ is slightly trickier. There are two asymmetric equilibria (which are the continuous limits of the equilibrium in Proposition 1), depending on which lender always makes an offer upon seeing a good signal. There is also a symmetric equilibrium where neither lender always makes an offer upon seeing a good signal (i.e., $m_s = m_w < 1$); and a continuum of asymmetric equilibria between either one of the two asymmetric equilibria and the symmetric one. In this class of equilibria, the pricing distribution is the same, except for the mass point—but the mass point plays the same role as the probability of not making offers. Lenders make a zero profit in any of these equilibria, but borrowers prefer the two asymmetric equilibria because there they are more likely to get a loan. For this reason, whenever this edge case matters, we focus on the two asymmetric equilibria that are the limiting cases of Proposition 1.

When τ goes to ∞ (i.e., when there is no default risk in the market), one can show that the equilibrium smoothly converges to the Bertrand equilibrium where both lenders offer $r = 0$, as expected. Another useful observation is that for $r \in [\underline{r}, \overline{r})$, the two distributions satisfy

$$F_s(r) = m_w F_w(r). \tag{7}$$

Since $m_w = 1 - \phi(\overline{r}) < 1$, this means the strong lender charges an interest rate higher than the weak lender in the sense of first-order stochastic dominance (FOSD). Intuitively, a good signal is not convincing enough for the weak lender to determine that the borrower is of high type, and so it chooses not to lend sometimes. As a result, the strong lender sometimes acts as the only credit supplier and charges a higher interest rate.

The following result reports how each lender's screening ability and average credit quality affect the competition.

Corollary 1. *In the competition equilibrium,*

1. *when the screening ability gap Δ increases or the average credit quality τ decreases, the strong lender's profit (which is also the industry profit) increases; and*
2. *when the strong lender's screening ability x_s improves, or the weaker lender's screening ability x_w deteriorates, or the average credit quality τ decreases, both lenders charge a higher interest rate in the sense of FOSD, and the weak lender makes an offer less frequently conditional on seeing a high signal.*

This result suggests that the winner's curse is the key driver of the degree of competition in our model. The winner's curse becomes more severe either for a larger screening ability gap Δ or a lower average credit quality τ, and both soften competition in equilibrium.

2.4 Borrower Surplus

The surplus of each type of borrowers is important for our subsequent analysis. Let $V_i(x_w, x_s, \tau)$ denote the expected surplus of an i-type borrower, $i \in \{h, l\}$, as a function of the two lenders' screening abilities and the average credit quality in the market.

A high-type borrower receives at least one offer (from the strong lender) and so always get a loan. The expected interest rate she pays is given by

$$(1 - m_w)\,\mathbb{E}[r_s] + m_w \mathbb{E}[\min(r_w, r_s)] = \underline{r} + (\overline{r} - \underline{r})\,\phi(\overline{r}), \tag{8}$$

where $\phi(\cdot)$ is defined as in (6). Here, when the weak lender does not make an offer, the borrower accepts the strong lender's offer; when both make offers, the borrower chooses the cheaper one. The equality comes from using $\mathbb{E}[r_s] = \underline{r} + \int_{\underline{r}}^{\overline{r}} \overline{F}_s(r)\, dr$ and $\mathbb{E}[\min(r_w, r_s)] = \underline{r} + \int_{\underline{r}}^{\overline{r}} \overline{F}_s(r)\, \overline{F}_w(r)\, dr$. Then a high-type borrower's expected surplus is

$$V_h(x_w, x_s, \tau) = (\overline{r} - \underline{r})(1 - \phi(\overline{r})), \tag{9}$$

which is the high-type's pecuniary payoff from the project and equals $\overline{r}$ net of the expected interest rate in (8). (Recall that we have normalized the high-type's nonmonetary benefit from getting a loan to zero.)[22]

Since a low-type borrower never pays back her loan, she cares only about the chance of getting a loan. A low-type borrower will not receive any offer if the strong lender observes a bad signal, and at the same time, the weak lender either observes a bad signal or observes a good signal but does not make an offer. This occurs with probability $x_s[x_w + (1 - x_w)(1 - m_w)]$. Therefore, given $m_w = 1 - \phi(\overline{r})$, a low-type borrower's expected surplus is

$$V_l(x_w, x_s, \tau) = \delta[1 - x_s(x_w + (1 - x_w)\phi(\overline{r}))], \tag{10}$$

where δ is the low-type's nonmonetary benefit from getting a loan as we have introduced earlier.

For our open banking applications, it is important to understand how each lender's screening ability affects borrower surplus.

Proposition 2. *Both types of borrower benefit from a higher average credit quality τ in the market. Regarding screening ability, both types of borrower suffer when the strong lender has a higher screening ability (i.e., a higher x_s); high-type borrowers benefit when the weaker lender has a higher screening ability (i.e., a higher x_w), but low-type borrowers benefit from a higher x_w if and only if $\frac{\overline{r}}{\underline{r}} < 1 + \sqrt{x_s}$.*

The first statement is straightforward from Corollary 1: A higher average credit quality lessens the winner's curse and so intensifies competition—lowered interest rates and/or higher chance that the weak lender makes an offer upon seeing a good signal (m_w increases)—which

[22] Here we use the interpretation that a borrower is a small business firm whose project yields a net return $\overline{r}$ when it succeeds. When a borrower is an ordinary consumer and she uses the loan to buy some consumption good which generates utility u, we have assumed an interest rate cap $\overline{r}$, in which case the expected surplus is $V_h(x_w, x_s, \tau) = u - \underline{r} - (\overline{r} - \underline{r})\phi(\overline{r}) = u - \overline{r} + (\overline{r} - \underline{r})(1 - \phi(\overline{r}))$. Since $u - \overline{r}$ is a constant, our analysis below carries over to this interpretation as well.

benefits both types of borrowers.

As for the second part, screening abilities affect borrower surplus via both the screening efficiency of detecting low types and the degree of lender competition. When x_s is higher, low types are more likely to be detected, which hurts low types;[23] but at the same time, the screening ability gap Δ widens and the weak lender suffers due to a more severe winner's curse, and a softer competition hurts both types of borrowers. On the other hand, when x_w is improved, screening efficiency improves but competition intensifies as the ability gap Δ shrinks. The high types benefit from both effects, but the low types can be ambiguously affected by these competing forces.

In general, a change in screening ability brings about an "information" effect that enhances the screening efficiency, and also a "strategic effect" that affects the equilibrium interest rate as well as the likelihood of a loan offer from the weak lender upon a good signal. These two effects can be more clearly seen if we rewrite the borrower surplus in the parameter space $\{x_w, \Delta, \tau\}$, in which case x_w is regarded as some base screening ability for both lenders, as formally stated in the next corollary. When x_w increases, both lenders' screening abilities improve, and intuitively this should benefit the high type and harm the low type. On the other hand, a widening of the screening ability gap Δ worsens the winner's curse problem, and this has a strategic pricing effect which lessens competition and impairs the welfare of borrowers.

Corollary 2. *Once expressed as functions of* $\{x_w, \Delta, \tau\}$*,* V_h *increases while* V_l *decreases in the base screening ability* x_w*, and both* V_h *and* V_l *decrease in the screening ability gap* Δ*.*

3 The Welfare Impact of Open Banking

From now on, we consider a competition between a traditional bank (denoted by b) and a fintech lender (denoted by f). We aim to examine the welfare impacts of open banking. We first consider the case when the data sharing is mandatory (i.e., the data will be shared even without customers' consent), and then consider the case of voluntary sign-up for data sharing as it works in practice.

[23] The improved screening efficiency has no effect on the high types, as the strong lender absorbs all the rent by enjoying increased profits.

3.1 Open Banking and Lenders' Information Technology

We assume that before open banking regulation, the bank is better at screening borrowers because of its rich data from existing bank-customer relationships. More specifically, let x_j, $j \in \{b, f\}$, be lender j's screening ability. We assume $x_f < x_b$ before open banking. After open banking, if the fintech has access to customer data from the bank, we assume that its screening ability improves significantly to x'_f so that it exceeds the traditional bank's ability x_b. This is because, for example, the fintech is often equipped with more advanced technology to make use of the data, or it has some additional customer information (e.g., from social media) that complements the bank data. Therefore, in this section we assume

$$x_f < x_b < x'_f. \tag{11}$$

It is useful to compare open banking to the common practice of credit reports provided by credit score agencies. First, as mentioned in Appendix B, credit scores or credit histories do not reflect bank account transaction information, the major data category that is currently locked inside incumbent banks and targeted by open banking. Given that traditional lenders heavily rely on credit reports for their loan-making businesses, the information from credit scores can be treated as public information among lenders and it determines the prior of a borrower's credit quality measured by τ in our model. In this sense, the market in our model should be regarded as a segment of borrowers who have similar credit scores.

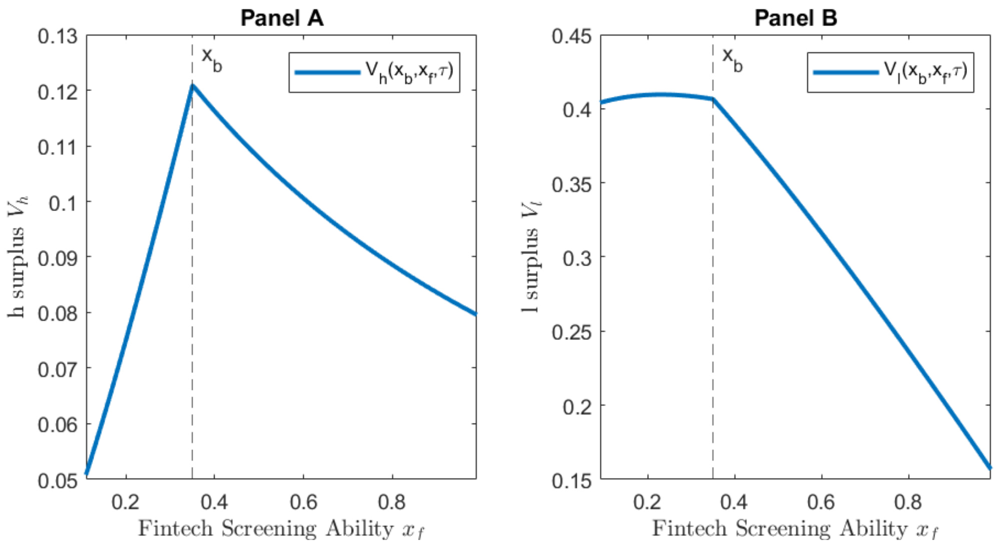
Second, perhaps more importantly, according to Fair Credit Reporting Act (FCRA) you have given lenders your consent to access to your credit report when you apply for credit,[24] but lenders need to "buy" credit reports from credit agencies. It is, therefore, a story of lenders' costly information acquisition, a mechanism well-studied by existing literature, rather than the case in which borrowers control their own data, as emphasized in this paper. This is what is behind UltraFICO mentioned in the Introduction; any lender can pull a borrower's FICO score when she applies for credit, but an UltraFICO score is only generated if the borrower opts in to share her account information.

3.2 Mandatory Sign-Up

Suppose first that all borrowers are required to sign up for open banking. This improves the fintech's screening ability, but it does not cause market segmentation since all borrowers

[24] Item [15 U.S.C. § 1681b], Fair Credit Reporting Act.

Figure 1: Borrower Surpluses when Fintech Screening Ability x_f Varies



High-type borrower surplus (Panel A) and low-type borrower surplus (Panel B). We plot the borrower surplus of both types as functions of the fintech lender's screening ability x_f. The high-type borrower surplus $V_h(x_b, x_f, \tau)$ is single-peaked at $x_f = x_b$ (hence $\Delta = 0$) while $V_l(x_b, x_f, \tau)$ is hump-shaped in the range of $x_f < x_b$. Parameter values are $\overline{r} = 0.36$, $x_b = 0.35$, $\delta = 0.5$, and $\tau = 3.4$.

have to share their data, so the lenders' prior beliefs of the average credit quality remain unchanged. This is not the practice of open banking regulation, but it is a useful benchmark.

Before open banking, the traditional bank is the strong lender and earns a positive profit $\frac{\Delta}{1+\tau} = \frac{x_b - x_f}{1+\tau}$, and the fintech earns a zero profit; after open banking, the fintech becomes the strong lender and earns a positive profit $\frac{\Delta'}{1+\tau} = \frac{x'_f - x_b}{1+\tau}$, and the bank earns a zero profit. Therefore, open banking increases industry profit if and only if it widens the screening ability gap between the two lenders (i.e., if $\Delta' > \Delta$).

Open banking increases the weak lender's screening ability from x_f to x_b and may expand or shrink the screening ability gap between the two lenders. So its impact on borrowers is less straightforward. Open banking benefits borrowers of type $i \in \{h, l\}$ if and only if $V_i\left(x_b, x'_f, \tau\right) > V_i(x_f, x_b, \tau)$. (Recall that the first dependent variable in the borrower surplus function is the weak lender's screening ability.) Proposition 2 implies that for a fixed x_b, (i) V_h increases in $x_f < x_b$ but decreases in $x_f > x_b$, and (ii) V_l can vary with $x_f < x_b$ nonmonotonically but must decrease in $x_f > x_b$. Figure 1 depicts a numerical example of how V_h (Panel A) and V_l (Panel B) vary with x_f for $x_b = 0.5$.

Therefore, as revealed by the above numerical example, if x_f is sufficiently close to x_b

before open banking and x'_f is sufficiently greater than x_b after open banking, both types of borrowers suffer due to open banking. In other words, open banking is detrimental to all borrowers if it causes a significantly larger new asymmetry between lenders. It is also useful to think of the borrower surplus problem from the perspective of the base screening ability x_w and the ability gap Δ as in Corollary 2. Open banking improves the base screening ability, which benefits the high-type but harms the low-type. Hence, the high-type will suffer due to open banking only if it widens the gap (i.e., if $\Delta' > \Delta$), in which case the low-type must suffer due to open banking and industry profit must be boosted.

In our setup, high-type borrowers always get a loan in either regime, implying that open banking is efficiency neutral to these borrowers. Low-type borrowers' surplus is proportional to the chance that they get a loan, and so whenever they suffer due to open banking, it must be that these low-type borrowers are less likely to get a loan (which improves the aggregate surplus if the low-type's private benefit from receiving a loan is $\delta < 1$).

The above discussion is summarized in the following result:

Proposition 3. *Compared to the regime before open banking,*

1. *for a fixed $x_b < 1$, there exist $\hat{x}_f < x_b < \hat{x}'_f$ such that open banking with mandatory data sharing harms all borrowers if $x_f \in [\hat{x}_f, x_b]$ and $x'_f \geq \hat{x}'_f$; and*

2. *open banking with mandatory data sharing helps the fintech but harms the bank, and whenever it harms all borrowers, it improves industry profit and market efficiency (if a low-type borrower generates an efficiency loss whenever she gets a loan).*

Here we have focused on the potential perverse effect of open banking on borrowers. Of course, for other configurations of the parameters it is possible for open banking to benefit one or both types of borrower. For instance, if x_f is sufficiently lower than x_b while x'_f is close to x_b, high-type borrowers benefit from mandatory sign-up, and in this case low-type borrowers benefit as well if $V_l\left(x_f = 0, x_b, \tau\right) < V_l\left(x_f = x_b, x_b, \tau\right)$ as in Figure 1.

3.3 Voluntary Sign-Up

Consistent with the spirit of GDPR in the EU (customers, rather than banks or firms more generally, own their personal data), recent open banking regulations in various countries give consumers the right to decide whether to allow fintech firms to access their personal banking data. But does this voluntary sign-up necessarily imply that consumers never get hurt? Consumers' sign-up decisions may reveal information on their credit quality, and this endogenous credit quality inference will influence the lenders' pricing strategies. As a result, it is ex ante unclear whether open banking with voluntary sign-up could hurt every consumer.

To facilitate our analysis where the equilibrium credit quality inference plays a key role, whenever we study the voluntary sign-up equilibrium, we suppose that borrowers have heterogeneous sign-up costs for open banking. More specifically, a fraction $\rho \in (0, 1)$ of borrowers, whom we call "non-tech-savvy," face an infinite sign-up cost and hence never sign up in equilibrium, while the remaining $1 - \rho$ of borrowers, whom we call "tech-savvy," have a zero sign-up cost and their sign-up decisions will be our focus. The sign-up cost is borrowers' private information, and for model parsimony, we assume it is independent of their credit quality type.

Although we label them based on "tech-savviness," we emphasize that the distribution of sign-up costs captures a wide range of heterogeneity among potential open banking customers. For instance, some consumers are technology savvy, so that they not only "understand" the concepts of how technology works but are also willing to "encompass" the utilization of such modern technology; some consumers may deeply worry about the security of sharing their own data due to some unpleasant personal experience. For instance, in the application of consumer credit, ρ is likely to be higher, for either privacy concerns or education background, relative to that of small businesses loans.

Introducing non-tech-savvy borrowers to our model not only captures the reality that some borrowers in practice are averse to open banking and data sharing for some non-economic reasons, but more importantly anchors the updated prior of credit quality in the opt-out market, which sharpens our equilibrium analysis. We will discuss the implication of $\rho > 0$ on the welfare effect of open banking in later sections; in fact, it tends to weaken the perverse effect that we are after.

3.3.1 Sign-up decisions and equilibrium characterization

Let $\sigma_i \in [0, 1]$, for $i \in \{h, l\}$, be the fraction of i-type tech-savvy borrowers who choose to sign up for open banking. Throughout, we use the two words "opt in" and "sign up" interchangeably (similarly, "opt out" is equivalent to "not sign up").

Consistent with open banking in practice, we assume that a borrower's sign-up decision is observable to both lenders.[25] Then the two lenders compete in two separate market segments:

[25] The fintech of course observes the sign-up decision. It is also easy for the traditional bank to monitor borrowers' sign-up decisions since in practice the fintech needs to use the API provided by the bank to access customer data.

one where borrowers sign up for open banking, and the other where borrowers do not. Let τ_+ and τ_- be respectively the lenders' updated prior on the average credit quality in the two market segments. Specifically,

$$\begin{cases} \tau_+ \equiv \frac{\Pr[h \mid \text{sign up}]}{1-\Pr[h \mid \text{sign up}]} = \tau \cdot \frac{\sigma_h}{\sigma_l} & , \\ \tau_- \equiv \frac{\Pr[h \mid \text{not sign up}]}{1-\Pr[h \mid \text{not sign up}]} = \tau \cdot \frac{1-(1-\rho)\sigma_h}{1-(1-\rho)\sigma_l} & . \end{cases} \tag{12}$$

Intuitively, when high-type tech-savvy borrowers are more likely to sign up for open banking, the lenders raise their estimate of the average credit quality in the opt-in segment but lower their estimate in the other. The presence of non-tech-savvy borrowers ensures that $\tau_- \geq \rho\tau$.

Anticipating the equilibrium sign-up decisions in the population and the subsequent competition outcome in each market segment, the sign-up decision of a tech-savvy borrower of credit quality type i is governed by:

$$\begin{cases} \sigma_i = 1, & \text{if } V_i\left(x_b, x'_f, \tau_+\right) > V_i\left(x_f, x_b, \tau_-\right), \\ \sigma_i \in [0,1], & \text{if } V_i\left(x_b, x'_f, \tau_+\right) = V_i\left(x_f, x_b, \tau_-\right), \\ \sigma_i = 0, & \text{if } V_i\left(x_b, x'_f, \tau_+\right) < V_i\left(x_f, x_b, \tau_-\right). \end{cases} \tag{13}$$

If a borrower chooses to sign up, she will be classified in the market segment characterized by $\left(x_b, x'_f, \tau_+\right)$ where the fintech becomes the strong lender; otherwise, she will be classified in the market segment characterized by (x_f, x_b, τ_-) where the fintech remains the weak lender. Note also that the surplus of an i-type non-tech-savvy borrower is $V_i(x_f, x_b, \tau_-)$, since she never signs up for open banking.

A perfect Bayesian equilibrium with voluntary sign-up is a collection of

$$\left\{\{\sigma_i\}, \{\tau_+, \tau_-\}, \left\{m_j^+, F_j^+\right\}, \left\{m_j^-, F_j^-\right\}\right\},$$

together with some off-equilibrium beliefs whenever appropriate, so that (i) $\{\sigma_i\}$ are the sign-up decisions of tech-savvy borrowers described in (13), (ii) $\{\tau_+, \tau_-\}$ are the lenders' updated prior on the average credit quality in each market segment as determined in (12), and (iii) $\left\{m_j^+, F_j^+\right\}$ and $\left\{m_j^-, F_j^-\right\}$ are the lenders' equilibrium pricing strategies in the corresponding market segments as described in Proposition 1, with qualifications for possible lender exits.

Two points are worth mentioning: First, as we will explain in detail in the proof of Proposition 4 below, a lender will become inactive in a market segment if the updated prior in that segment becomes so low that condition (1) fails to hold for that lender. In that case, the pricing equilibrium and the expressions for borrower surplus need to be modified but in a straightforward way. Second, if the lenders expect sign-up decisions $\sigma_l = 0$ and $\sigma_h > 0$, then they will regard any borrower who signs up as a high type. In this case, we assume that a creditworthiness test will still be conducted, and if a lender observes a bad signal, it will reclassify the borrower as low type.[26]

Notice that with voluntary sign-up, there is always an equilibrium in which nobody signs up for open banking, if we assign a sufficiently unfavorable off-equilibrium belief to whoever signs up for open banking. But this equilibrium is trivial in the sense that open banking has no impact at all on borrowers and lenders. In the following, we ignore this uninteresting equilibrium since there always exists a more meaningful equilibrium.

The following lemma helps narrow down the possible types of equilibrium. Intuitively, high-type borrowers are not afraid of a more precise screening technology, and so they are more willing to sign up than low-type borrowers. This result, which holds generally in any credit market model, also plays an important role in generating the perverse effect of open banking as discussed below in Section 3.3.2.

Lemma 2. *If low-type tech-savvy borrowers weakly prefer to sign up, then high-type tech-savvy borrowers must strictly prefer to sign up.*

Using this lemma, we show in the following proposition that there are only three possible types of (non-trivial) equilibrium, and in any equilibrium high-type tech-savvy borrowers sign up for sure.

Proposition 4. *Under condition (1), there exists a unique non-trivial equilibrium with voluntary sign-up. This non-trivial equilibrium falls into three possible types:*

1. $V_l\left(x_f, x_b, \tau\right) \leq V_l\left(x_b, x_f', \tau\right)$. *In the unique "pooling" equilibrium, all tech-savvy borrowers sign up for open banking regardless of their credit quality (i.e., $\sigma_l = \sigma_h = 1$).*

2. $V_l\left(x_f, x_b, \tau\right) > V_l\left(x_b, x_f', \tau\right)$ *and* $V_l\left(x_f, x_b, \rho\tau\right) < V_l\left(x_b, x_f', \infty\right)$. *In the unique "semi-separating" equilibrium, an endogenous fraction of low-type tech-savvy borrowers and all high-type tech-savvy borrowers sign up (i.e., $\sigma_l \in (0,1)$ and $\sigma_h = 1$).*

3. $V_l\left(x_f, x_b, \rho\tau\right) \geq V_l\left(x_b, x_f', \infty\right)$. *In the unique "separating" equilibrium, low-type tech-savvy borrowers never sign up while high-type tech-savvy borrowers sign up always (i.e., $\sigma_l = 0$ and $\sigma_h = 1$).*

[26] This can be justified if there are some open banking lovers who always sign up, or if we introduce some noise in borrowers' sign-up decisions in the spirit of sequential equilibrium.

We emphasize that this proposition is a full characterization of all possible (non-trivial) equilibria, as the three sets of conditions, which only depend on the primitive parameters, cover all possible parameter configurations.

In the pooling equilibrium (Proposition 4.1), if low-type borrowers benefit from open banking when the prior of credit quality remains unchanged, high-type borrowers must benefit as well. Then it must be an equilibrium in which all tech-savvy borrowers sign up. In the separating equilibrium (Proposition 4.3), the condition implies that low-type borrowers will never sign up: they do not want to even if the credit quality inference becomes the most favorable possible for opting-in.[27] Then in the opt-in market, all borrowers must be of high type and lenders compete in a Bertrand way, in which case high-type borrowers receive the highest possible surplus $\overline{r}$.

In semi-separating equilibrium (Proposition 4.2), notice that according to Lemma 2, all high-type tech-savvy borrowers will sign up in any equilibrium where some low types sign up. Given that high types sign up, if all low-type tech-savvy borrowers sign up, then the priors on credit quality in both the opt-in and opt-out markets remain unchanged ($\tau_+ = \tau_- = \tau$), in which case the first condition $V_l\left(x_f, x_b, \tau\right) > V_l\left(x_b, x'_f, \tau\right)$ implies that they would like to opt out due to the fintech's improved screening ability in the opt-in market. If none of the low-type tech-savvy borrowers sign up, the prior on credit quality in the opt-in market becomes the most favorable, in which case the second condition $V_l\left(x_f, x_b, \rho\tau\right) < V_l\left(x_b, x'_f, \infty\right)$ implies that they would like to join the opt-in market. As a result, low-type tech-savvy borrowers must play a mixed strategy in equilibrium, i.e., some of them will opt in and the others will not.

Before delving into the impact of open banking, we should explain the important role of the presence of non-tech-savvy borrowers (i.e., $\rho > 0$) in our model. If $\rho = 0$, we must have $\tau_- = 0$ in any non-trivial equilibrium as high-type borrowers always sign up. Then low-type borrowers will sign up as well. As a result of this standard unraveling argument, the only non-trivial equilibrium is the pooling equilibrium where all borrowers sign up and the outcome is the same as with mandatory sign-up.[28] As we will show shortly that the voluntary feature of open banking does help borrowers to some extent, allowing for $\rho > 0$ tends to weaken the perverse effect that we are after.

[27] Recall that we assume that the creditworthiness test (which is costless) will always be conducted, so low-type borrowers might be screened with some probability independent of τ_+.

[28] One needs to specify a proper off-equilibrium belief to sustain the equilibrium if the condition $V_l(x_f, x_b, \tau) \le V_l(x_b, x'_f, \tau)$ does not hold.

3.3.2 The impact of open banking

The following result reports the impact of open banking:

Corollary 3. *Compared to the case before open banking,*

1. *in the pooling equilibrium (Proposition 4.1) or the separating equilibrium (Proposition 4.3), at least some borrowers benefit from open banking. In the former case, all tech-savvy borrowers get better off and non-tech-savvy borrowers remain unaffected; in the latter case, all opting-out borrowers get worse off while all opting-in borrowers better off.*

2. *in the semi-separating equilibrium (Proposition 4.2), non-tech-savvy borrowers and low-type tech-savvy borrowers get worse off. It is possible that high-type tech-savvy borrowers also get worse off, so all borrowers are hurt by open banking.*

3. *if all borrowers suffer due to open banking and both lenders are active in the opt-out market, the bank loses and the fintech gains, industry profit improves, and market efficiency improves as well (if a low-type borrower generates an efficiency loss whenever she gets a loan).*

The result in the first pooling equilibrium is straightforward. In the third separating equilibrium, opting-in reveals high type, while opting-out signals worse credit quality than population $\tau_- = \rho\tau < \tau$. Hence, open banking benefits only the high-type tech-savvy borrowers who receive the maximum surplus $\bar{r}$, and hurts all other borrowers who opt out.

The second result in the semi-separating equilibrium points to the perverse effect of open banking. Sign-up decision itself signals for credit quality. Hence, for those borrowers who opt out, they must get worse off from the unfavorable inference $\tau_- < \tau$. For those low-type tech-savvy borrowers who sign up, since they are indifferent about signing up or not, they must get worse off as well. For those high-type tech-savvy borrowers, although they are viewed more favorably ($\tau_+ > \tau$), they might face softened competition and could still suffer due to open banking.

More precisely, all borrowers suffer due to open banking if and only if the following conditions are satisfied:

$$V_h\left(x_f, x_b, \tau_-\right) \leq V_h\left(x_b, x'_f, \tau_+\right) < V_h\left(x_f, x_b, \tau\right), \tag{14}$$

and

$$V_l\left(x_f, x_b, \tau_-\right) = V_l\left(x_b, x'_f, \tau_+\right), \tag{15}$$

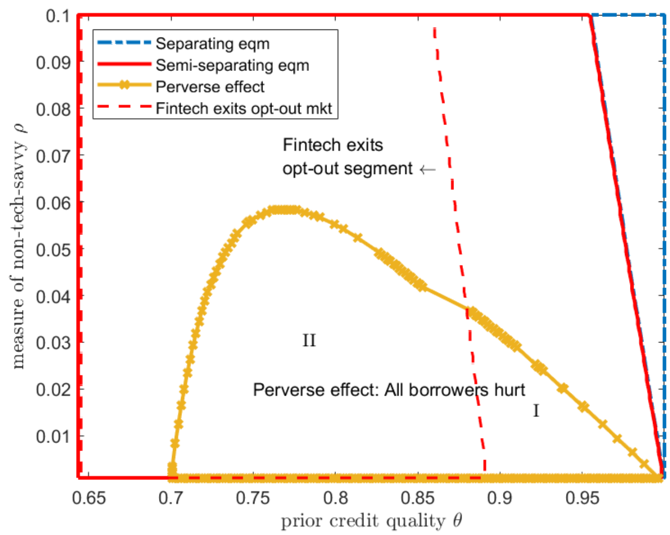
where $\tau_- = \frac{\rho\tau}{1-(1-\rho)\sigma_l} < \tau < \tau_+ = \frac{\tau}{\sigma_l}$ as we have $\sigma_h = 1$ in the second equilibrium. (These conditions ensure the semi-separating equilibrium, with the second inequality in (14) as the extra condition for high-type tech-savvy borrowers to be worse off.) As both V_h and V_l increase in the prior on credit quality, conditions (14) and (15) can hold only if $V_h\left(x_b, x'_f, \tau\right) < V_h\left(x_f, x_b, \tau\right)$ and $V_l\left(x_b, x'_f, \tau\right) < V_l\left(x_f, x_b, \tau\right)$, i.e., only if all borrowers suffer due to mandatory sign-up. (Recall that in this case we must have $\Delta' = x'_f - x_b > \Delta = x_b - x_f$.) Consequently, as compared with mandatory sign-up, the voluntary feature protects borrowers from the potential harm of open banking in some cases, but it does not eliminate this possibility completely.

It is worth emphasizing that Lemma 2, which says that high-type borrowers are more willing to sign up for open banking than their low-type peers, is crucial in generating the perverse effect. The thrust of that lemma is that opting into open banking signals high credit quality. If this were not true, the high-type would never be hurt by open banking, as opting-out would not cause impairment to their perceived credit quality.

Another interesting observation is that non-tech-savvy borrowers *always* (weakly) suffer due to open banking with voluntary sign-up. Again, this is due to the adverse inference in the opt-out market (Lemma 2): in the pooling equilibrium they remain unaffected, while in the other two equilibria they get strictly worse off. The selection behavior of the tech-savvy borrowers—more specifically, high-type borrowers are more willing to opt in than low type ones—imposes a negative externality on the non-tech-savvy borrowers. One particularly relevant interpretation of our non-tech-savvy borrowers is that some will have strong intrinsic privacy concerns, and our analysis complements Aridor, Che, and Salz (2020) in that whoever embraces the new technology exerts negative externality on those who are left behind.

Finally, we comment on how open banking affects profit and overall welfare. When both market segments have two active lenders, both lenders make a positive profit (the bank earns from the opt-out market segment and the fintech earns from the opt-in market segment), but the bank earns less than before. When high-type borrowers also suffer due to open banking, similarly as in the case of mandatory sign-up, open banking must have sufficiently widened the screening ability gap Δ' from Δ. As a result, the total industry profit must rise in this situation at the expense of borrowers, which is contrary to the original intention of open banking regulations.

Figure 2: Voluntary Sign-Up Equilibrium



The range of various non-trivial voluntary sign-up equilibria in the parameter space of $\left(\theta = \frac{\tau}{1+\tau}, \rho\right)$. The red solid line illustrates the case of semi-separating equilibrium, and the blue dash-dot line illustrates the separating equilibrium. Within the semi-separating equilibrium, the red dashed line illustrates a transition of lender participation in the opt-out segment: fintech becomes inactive for θ lies to the left of this line. The yellow crossed line illustrates the area where both types of borrowers are hurt by open banking despite voluntary sign-up. Parameters: $\overline{r} = 0.36$, $x_b = 0.4$, $x_f = 0.35$, and $x_{f'} = 0.8$. (In this configuration of parameters there is no pooling equilibrium; condition (1) holds always.)

3.3.3 Credit quality inference and potential perverse effect

Figure 2 highlights the role of the credit quality inference in determining the type of equilibrium and borrower surplus. We examine both the level of credit quality prior as measured by θ, the fraction of high-type borrowers in the market, as well as the sensitivity as measured by the fraction of non-tech-savvy borrowers ρ, while keeping fixed the lender screening technologies that has a widening gap after open banking.

When the credit quality $\theta = \frac{\tau}{1+\tau}$ is high and more borrowers are non-tech-savvy, opting-out does not result in a large deterioration in credit quality inference, so the separating equilibrium arises in which low types opt out, as shown on the upper-right corner with blue dash-dotted boundaries in Figure 2. For lower credit quality θ, we enter the lower-left region with red solid boundaries, where a semi-separating equilibrium arises and low types are just indifferent about sign-up decisions. In the specific parameter configuration of Figure 2, there is no pooling equilibrium.

The yellow crossed lines depict the region of the perverse effect of open banking. The effect of ρ is straightforward: the smaller the fraction of non-tech-savvy borrowers, the more sensitive the credit quality inference regarding the sign-up decisions; this sensitivity opens the room for perverse effect even when borrowers control the information as explained in Section 3.3.2. This situation arises in region I at the bottom-right corner in Figure 2.

For an even lower prior credit quality θ, the endogenous credit quality in the opt-out segment deteriorates so much that it might even lead to an inactive fintech there–as shown in region II in Figure 2, only the traditional bank serves the opt-out borrowers. That the fintech exits the opt-out market after open banking, which might occur due to other practical reasons outside this model (e.g., capacity constraint), contributes further to the perverse effect that we are highlighting. To see this, in response to inactive fintech in the opt-out market, a larger fraction of low types sign up for open banking so that they are still indifferent in equilibrium. The chain reaction is that this makes tech-savvy high types suffer due to open banking, as they are pooled with more low types and the effect of softened competition dominates.

Similar patterns as in Figure 2 arise for many other parameter configurations where $\Delta' > \Delta$. A message from this numerical exercise, which is relevant to policy making, is that the perverse effect of open banking occurs most likely in the market where borrowers are likely to embrace the open banking technology (small ρ), and with a relatively low average credit quality (low τ, so that the fintech may exit in the opt-out market). Though the second result regarding τ applies to both applications of consumer credit and small business loans, the first result on ρ seems imply that the perverse effect is more likely to occur in the small business loan market (where non-economic privacy concerns are less severe.)

4 Extensions and Discussions

This section considers three extensions to our baseline model: multiple fintech lenders, borrowers' affinities toward fintech loans, and what if open banking shares borrowers' preference data to fintechs. Each of them has important implications on the potential perverse effect of open banking, and we organize our discussions around this focal point.

4.1 Multiple Fintech Lenders

We have adopted the simplest model structure—two lenders—to study credit market competition, which is consistent with search friction in practice.[29] However, open banking could substantially enlarge the consideration set of borrowers (Clark, Houde, and Kastl, 2020) by alleviating search frictions and/or promoting inclusive financing to borrowers who only have online footprints, but not bank accounts.

The number of lenders matters for our analysis, in that the perverse effect from sharing credit quality data crucially relies on softened competition after open banking. So a natural question is: Will the economy be free from the potential perverse effects on borrowers once we have multiple fintech lenders?

The number of lenders per se does not eliminate perverse effects; in fact, in standard credit market competition models featuring information asymmetry, there will be at most two active lenders in equilibrium whenever lenders differ in screening abilities. Say there are three lenders, i.e., one bank and two fintechs; when lenders differ in lending costs (due to winner's curse) but offer identical products, it is impossible for all three to survive (for a formal proof, see Online Appendix C). The winner's curse causing a barrier to entry is also familiar in the literature; see, e.g., Dell'Ariccia, Friedman, and Marquez (1999), Marquez (2002), and Rajan (1992). Hence, under mandatory open banking, if the two active lenders' screening abilities are far apart from each other after obtaining borrowers' banking data, the perverse effect still arises.

With voluntary sign-ups, multiple fintechs allow borrowers to strategically choose favorable fintechs with whom to share data. However, equilibrium beliefs may force low types to "follow" high types and discourage high types from choosing certain fintechs to share data with, which in turn renders the extra fintech options as useless.

Therefore, the key driver of the perverse effect is the potential large gap in screening abilities. In our three-lender example, this is likely to arise, if one fintech is a big-tech say Ant Financial while the other fintech is a start-up company in niche markets. In the other extreme, in our Online Appendix C, we study an example with one bank and two symmetric (both before and after open banking) fintechs. All three lenders are present before open banking, while the bank exits facing two stronger fintechs after open banking. The perverse effect is eliminated in this case, which is the most favorable situation from a regulator's perspective: Improved screening ability increases total welfare, but financial industry profits

[29] For instance, Allen, Clark, and Houde (2014) show that in Canada borrowers who search for more than a single mortgage quote negotiate with 2.25 financial institutions on average.

drastically drop to zero, so the borrower surplus must go up.

4.2 Fintech Affinities

Besides the algorithmic screening, fintech lending has a different nature of customer-lender interaction. The automated processing not only makes fintech loans more swift, involving less steps and quicker approval decisions (e.g., Fuster, Plosser, Schnabl, and Vickery, 2019), but also allows for niche products such as tailored financing options (say "Buy Now Pay Later"), platform-based lending (e.g., SoFi provides one-shop-for-all services), and small business loans based on payment network (e.g., Square loans are automatically repaid by sales). All these business practices imply that fintech lenders enjoy certain monopoly power thanks to their ability to provide better or tailored services (e.g., Buchak, Matvos, Piskorski, and Seru, 2018).

In our baseline model, open banking creating a large gap in screening abilities is necessary for the perverse effect to emerge. This section shows that the borrowers' affinity toward fintech loans, which generally gives fintech lenders certain market power, reduces the required gap in screening abilities for the perverse effect to emerge.

4.2.1 Model extension with fintech affinities

There are many ways to introduce the borrower's affinity toward fintech loans; the following setting involves minimal modifications to our baseline while still capturing the essence of fintech affinity. Consider the revision that each borrower is subject to a preference shock *ex post*: With a probability $\xi \in [0,1)$, the borrower receives only ϵ utility from the bank loan with $\epsilon \to 0$. For simplicity, we will call this preference shock ξ-event, and later refer to ξ as fintech affinity. Under the extension with fintech affinity, borrowers in the ξ-event will for sure take the fintech offer if they receive an offer from the fintech, independent of the bank offer (i.e., whether they received the bank offer, and if yes, the details of the bank offer); they, however, will take the bank loan if that is the only offer.

One potential interpretation of the ξ-event is that bank loan processing takes lengthy time and the borrower becomes impatient. More broadly, these borrowers hit by the preference shock are similar to the "captured" consumers in Varian (1980), which gives the fintech local monopoly power. For simplicity, the ξ-event is independent of the borrower's credit quality type and is unobservable to both lenders; Section 4.3 considers the situation where the observability is affected by open banking.

Suppose that before open banking the weaker fintech's screening ability x_f is sufficiently low (compared to the bank), so that the fintech still earns a zero profit even with the captured event. The bank's indifference condition is

$$p_{HH}\left[1-m_f+\underbrace{m_f\overline{F}_f\left(r\right)\cdot\left(1-\xi\right)}_{\text{when both lenders compete, } r_f>r}\right]\left[\mu_{HH}\left(1+r\right)-1\right]-\underbrace{p_{HL}}_{\text{winner's curse}}=\pi_b. \tag{16}$$

Compared with Eq. (3), here when lenders compete (both lenders see good signals, with prob. p_{HH}, and the fintech makes an offer, with prob. m_f) and even if the bank's quote is lower ($r_f>r$, with prob. $\overline{F}_f(r)$), the bank gets the borrower only with probability $1-\xi$. In contrast, the preference shock $(1-\xi)$ will not hit the case of winner's curse—only the bank wrongly screens a low type as H (with prob. p_{HL}), because in this case the bank is the only lender making the offer. This immediately implies that the fintech affinity exacerbates the bank's winner curse: Conditional on the bank receiving a good signal ($S_b=H$), fintech affinity disproportionately hurts the bank in competition for a potentially profitable borrower but never helps the bank in avoiding lemons when there's winner's curse.

For the fintech, the indifference condition becomes

$$p_{HH}\left[\xi+\left(1-\xi\right)\overline{F}_b\left(r\right)\right]\left[\mu_{HH}\left(1+r\right)-1\right]-p_{LH}=\pi_f. \tag{17}$$

Comparing this to Eq. (4), one observes that in the event of both lenders seeing good signals (with prob. p_{HH}), the probability of the (stronger) bank not making an offer, which equals $1-m_b$, is replaced by the probability of fintech affinity ξ. Put it differently, in the ξ-event the fintech gets borrowers for sure as if the bank does not make any offer. Of course, in the baseline the (stronger) bank endogenously chooses to make offer always so that $1-m_b=0$ in Eq. (4), while in Eq. (17) $\xi>0$ is an exogenous parameter capturing the fintech affinity.

The above indifference conditions apply when the fintech has relatively weak screening ability; we relegate the corresponding conditions after open banking when the fintech has relatively stronger screening ability to Appendix. We then repeat the same analysis as in Section 3, taking into account of the endogenous sign-up decisions by borrowers. Proposition 5 provides a characterization of the equilibria with fintech affinity.

Proposition 5. *For a relatively small fintech affinity $\xi>0$, the equilibrium is characterized by follows.* ***to be added.***

4.2.2 The perverse effect of open banking: revisited

When borrowers exhibit fintech affinity, the perverse effect of open banking becomes more likely to occur. The important take-away is that a large lead in fintech's screening ability (potentially boosted by open banking) is not necessary for the perverse effect.

To see this intuitively, let us revisit Figure 1 under our baseline model. As clear from the discussion in Section 3.3.2, the key of perverse effect is to check the impact of open banking on the high type's surplus V_h, which we plot in Panel A as a function of fintech's screening ability x_f while fixing the bank's screening ability x_b. Corollary 2 shows that V_h reaches its peak when x_f hits x_b exactly, i.e., there is no screening ability gap $\Delta = |x_b - x_f| = 0$. As explained in Section 2.4, a zero screening ability gap results in the strongest competition and hence delivers the highest surplus to high type borrowers.

We index $V_h(x_f; \xi)$ by the fintech affinity ξ; the baseline model corresponds to the case of $\xi = 0$. Further denote by $\hat{x}_f(\xi)$ the threshold fintech screening ability at which $V_h(x_f; \xi)$ reaches its peak, i.e., $V_h(\hat{x}_f(\xi); \xi) > V_h(x_f; \xi)$ for all x_f. The above discussion implies that $\hat{x}_f(\xi = 0) = x_b$. Would the fintech affinity lower $\hat{x}_f(\xi) < x_b$ so the high types' surplus starts to fall earlier?

The answer is yes. We derive the fintech's offer probability and the bank's profit, both indexed by ξ, by evaluating the bank's indifference condition (16) at $\underline{r}$ and $\overline{r}$:

$$m_f(\xi) = \frac{1 - \phi(\overline{r})}{1 - \xi\phi(\overline{r})}, \text{ and } \pi_b(\xi) = \frac{1}{1+\tau}\left[\frac{1-\xi}{1-\xi\phi(\overline{r})}x_b(1-x_f) - x_f(1-x_b)\right]. \tag{18}$$

Both are consistent with Proposition 1 which characterizes the equilibrium in baseline model (i.e., when $\xi = 0$), with $m_f(\xi = 0) = 1 - \phi(\overline{r})$ and $\pi_b(\xi = 0) = \frac{\Delta}{1+\tau} = \frac{x_b - x_f}{1+\tau}$. Given $x_f < x_b$ and $\phi(\overline{r}) < 1$, one can show $m_f'(\xi) > 0$ and $\pi_b'(\xi) < 0$. Intuitively, the greater the fintech affinity ξ, the greater the fintech's monopoly power, hence the higher the probability of fintech offers and the lower the bank profit.

In the baseline, we have used the non-negative bank profit condition to derive the threshold $\hat{x}_f(\xi = 0) = x_b$. Now with fintech affinity, the bank suffers a more severe winner's curse; therefore, bank profit drops to zero strictly before the fintech catches up with the bank's screening ability. In fact, from Eq. (18), we know that $\hat{x}_f(\xi)$ solves the following zero bank profit condition (writing the dependence of $\phi(\bar{r}; x_b, x_f)$ on x_b and x_f explicitly):[30]

$$\frac{1-\xi}{1-\xi\phi\left(\bar{r}; x_b, \hat{x}_f(\xi)\right)} = \frac{\hat{x}_f(\xi)\cdot(1-x_b)}{x_b\left(1-\hat{x}_f(\xi)\right)}. \tag{19}$$

Importantly, $\hat{x}_f(\xi) \leq x_b$ when $\xi \geq 0$,and the inequality is strict when $\xi > 0$. This implies when the fintech's screening ability increases as a consequence of open banking, the high type borrowers' surplus start to fall before the fintech's screening ability catches up with the bank's. Intuitively, fintech affinity, which represents the fintech's innate strength, can supplement the required screening ability gap Δ for the perverse effect of open banking to emerge.

DRAW A FIGURE SHOW THAT THE REGION OF PERVERSE EFFECT GETS LARGER WITH $\xi > 0$.

4.3 Open Banking: Preference Data and Targeted Loans

We so far have focused on sharing data on borrowers' credit quality. However, the data that modern financial institutions process are multidimensional, and contain information on other aspects of customer behavior, say their preferences. Such extra information can be particularly valuable for fintech companies given their more advanced "big data" technology, which could potentially hurt customers. Broadly related to consumer privacy, this category of information complements well the information on credit quality studied in Section 3.

Exactly out of such concerns, many regulators around the world mandate consent from customers themselves when sharing their data. This section shows that this cannot fully protect consumer borrowers even if they control their own data, again because noncredit data sharing is intertwined with credit quality inference as we have shown in the previous section. Therefore one important take-away is that the perverse effect of open banking does not necessarily need a large gap in screening abilities, once we recognize that the shared data could be beyond credit quality information.

The following discussions draw heavily in the working paper version of this paper (NBER WP28118), which takes the setting in Section 4.2 but changes the information content of open banking. Before open banking, the fintech cannot observe this ξ-event. With open banking, however, this ξ-event (for borrowers signed up for open banking) becomes perfectly

[30] One can easily check that the left hand side (right hand side) of Eq. (19) is decreasing (increasing) in x_f, therefore the bank is making a positive profit when x_f increases from left toward $\hat{x}_f$.

observable to the fintech lender who then know exactly when borrowers are "locked in" to fintech loans.[31]

For simplicity we further assume that in ξ-event the borrower can only take fintech loans. Albeit stark, our modeling of ξ-events is motivated by "event-based marketing," and captures the idea that open banking enables fintech lenders to perform "precision marketing" by combining the borrower's newly accessible banking transaction records with some other existing information (e.g., the borrower's social media data).[32] Precision marketing in our setting fall into two broad categories. First, some borrowers strongly prefer fintech loans. Imagine a consumer with a strong preference for "immediacy" on some e-commerce platform, and fintech lenders often dominate traditional banks by processing loan applications much faster. With open banking, the transaction records from the borrower's bank (which reveals the borrower's consumption habits), together with the borrower's digital footprint, often enable the fintech lender to better identify the borrowers' demand immediacy. In the second category, borrowers face a restricted set of available lenders in some circumstances; a borrower could be ineligible for bank loans sometime, or she travels abroad and needs an emergency loan in foreign currency (say for health insurance) unavailable from her bank.[33]

To highlight the new role of open banking, we assume that the fintech lender's screening ability on credit type remains unchanged (i.e., $x_f' = x_f$) after open banking. We fully characterize the equilibrium outcome as a function of ξ, and show a similar welfare result as

[31]It is worth emphasizing that only the fintech's observation of ξ-event matters. The bank knows that it has no chance to win a borrower in her ξ-event anyway, whether or not the bank observes this event.

[32]Precision marketing is a broader idea in retail business. Doug Shaddle, Director of Sales for UberMedia, once said that "the adoption of mobile technology is creating new data streams that can provide retailers with an unprecedented amount of information about who their shoppers are and how to bring them further into the fold, ... to deliver the right offer, at the right time, to the right customer." (See `https://bwnews.pr/2FBXeA3`.) Of course, broadly speaking, precision marketing could play a role for our study of credit information in Section 3 if the fintech, due to its superior technology, can classify borrowers into more categories after open banking and so tailor more personalized offers. It is an interesting direction for future research.

[33]We assume that these ξ-events are realized *ex post*, after borrowers have made their sign-up decisions; this way, the belief updating with regard to the borrower's opt-in/opt-out decision is only on credit quality, just like in Section 3. Our previous real-world examples are chosen to highlight the idiosyncratic nature of these preference events. Although GDPR requires that users shall be provided with the opportunity to change their minds and revoke consent, in practice customers often decide once and for all whether to opt in or opt out of open banking when they start using the fintech services; case-by-case decisions likely involves a prohibitively high attention cost. Indeed, a recent regulatory move by UK authorities streamlines open banking by axing 90-day re-authentication mandate. Even if one can swiftly opt out of open banking "without strings attached" as described in the Deloitte Insight survey in the introduction, borrowers are unlikely to know exactly what data will be useful for the fintech, without mentioning that it might be too late to opt out as they have consented to sharing their recent banking history.

in Section 3: All borrowers may be hurt by open banking in equilibrium. This happens for an intermediate probability of preference events; loosely speaking, those who sign up suffer due to being exploited in the captured events; those who do not suffer due to an unfavorable credit quality inference.

5 Conclusion

As the volume of data created by the digital world continues to grow, customer data have evolved into a defining force in every aspect of the banking business. Open banking regulations that require banks to share their existing customers' data with third parties—notably, fintech lenders—at customers' requests can be viewed as an integral part of the broader "open economy" initiative, in which data should be open to outside third parties at the consent of customers who generate them.

We offer the first theoretical study on the consequences of letting borrowers control their own data in an otherwise classic credit market competition between an incumbent traditional bank and a challenger fintech lender. Though consistent with the premise that open banking favors challenger fintechs, which perhaps benefits some or all customers via enhanced competition, our results highlight that the voluntary nature of data sharing is not sufficient to protect borrowers' welfare. Whether data sharing under open banking are concerning borrowers' creditworthiness or their preferences, we show the general existence of scenarios in which all borrowers are strictly worse off, even for those who opt out of open banking. This perverse effect is driven by the credit quality inference from borrower's "sign-up" decisions, which is rooted in adverse selection as the backbone of credit market competition. Broadly, this effect is consistent with the information externality caused by consumer decisions, which poses a long-standing challenge to regulations on consumer protection in the modern financial industry.

There are a few other important issues related to open banking that we leave for future research. First, traditional banks operate not only in the lending market but also in the deposit and payment service markets. Open banking affects their competition with fintech challengers in the latter markets as well, leading to another potential perverse effect on consumers. For instance, as the transaction account service provides the most valuable data for traditional banks, data sharing required by open banking may dampen their incentives to compete in that market. Second, from a long-term perspective, should successful fintech giants also be required to share data back with traditional banks? Last but not least, we take open banking regulation as given; but is it better than the market mechanism where traditional banks acquire fintech challengers, or act as data brokers and sell their data (with customer consent) to fintechs?

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A Proofs

A.1 Notation Summary

Table 1: Notation Summary

Notation	*Definition and Meaning*	*Characterization*
θ	Probability of high-type	
τ	Likelihood ratio of high-type	$\tau = \frac{\theta}{1-\theta}$
ρ	Proportion of non–tech-savvy borrowers	
$\mu_i,\ i \in \{h, l\}$	Probability that a high/low-type repays	$\mu_h = 1$
$\delta_i,\ i \in \{h, l\}$	Borrower's private benefit of receiving a loan	$\delta_h = 0, \delta_l = \delta > 0$
$V_i(x_w, x_s, \tau)$	Borrower i's surplus	
$j \in \{b, f, s, w\}$	Lender: traditional *b*ank, or *f*intech; *s*trong, or *w*eak	
$S_j \in \{H, L\}$	Signal of lender j, is H or L	
x_j	Screening ability of lender j in "bad news" structure	$\mathbb{P}(S_j = L\|l) = x_j$
$p_{HH}, p_{HL}, p_{LH}, p_{LL}$	Probabilities of lender signals	
$\mu_{HH}, \mu_{HL}, \mu_{LH}, \mu_{LL}$	Probabilities of repayment for borrowers with given signals	
$\overline{r}$	Upper bound of net interest rate (exogenous)	
$\underline{r}$	Lower bound of net interest rate	
m_j	Probability that lender j grants a loan given $S_j = H$	
r_j	Net interest rate offered by lender j	
$F_j(r); \overline{F}_j(r)$	CDF of r_j; survival function of $F_j(r)$	$\overline{F}_j(r) = 1 - F_j(r)$
λ_j	The mass point of $F_j(r)$ at $\overline{r}$	$\lambda_j = \lim_{r \uparrow \overline{r}} \overline{F}_j(r)$
π_j	Lender j's profit	
$\phi(r)$		Eq. (6)
Δ	Gap in screening ability	$\Delta = x_s - x_w$
x'_f	Screening ability of fintech after open banking in Section 3	
$\sigma_i,\ i \in \{h, l\}$	Proportion of type i tech-savvy borrowers who opt in	
τ_+, τ_-	Updated prior of borrowers who opt in (+), and who opt out (-)	
ξ	Probability of privacy event	
$p(\xi)$	Population of opt-in borrowers in Section **??**	

A.2 Proof of Lemma 1

Proof. Suppose first that $\pi_s, \pi_w > 0$ in equilibrium. Then both lenders make an offer for sure upon seeing a good signal (i.e., $m_s = m_w = 1$). As $r \uparrow \overline{r}$, at least one of $\overline{F}_s(r)$ and $\overline{F}_w(r)$ will be zero since it is impossible that both distributions have a mass point at $r = \overline{r}$ in equilibrium. Suppose $\overline{F}_w(\overline{r}) = 0$. Then the strong lender's indifference condition (3) implies that $\pi_s = -p_{HL} < 0$, which is a contradiction.

Suppose then $\pi_w \geq \pi_s = 0$. Then at $r = \underline{r}$, we must have $\overline{F}_w(r) = \overline{F}_s(r) = 1$, and so we need $p_{LH} \leq p_{HL}$ to make both indifference conditions hold. But as we pointed out before this cannot be true given $x_s > x_w$. Therefore, the only remaining possibility is that $\pi_s > \pi_w = 0$. □

A.3 Proof of Proposition 1

Proof. We know the strong lender's distribution is $\overline{F}_s(r) = \phi(r)$. From $\overline{F}_s(\underline{r}) = 1$, we solve $\underline{r} = (1 - x_w)/\tau$, which is less than $\overline{r}$ given condition (1). The size of F_s's mass point is $\lambda_s = \phi(\overline{r})$, which is less than 1 given condition (1). Letting $r = \underline{r}$ in (3) yields $\pi_s = p_{LH} - p_{HL} = (1-\theta)\Delta = \frac{\Delta}{1+\tau}$, and letting $r = \overline{r}$ in (3) yields $1 - m_w = \phi(\overline{r})$. Finally, $\overline{F}_w(r)$ is solved from (3). □

A.4 Proof of Corollary 1

Proof. (i) Given $\pi_s = \frac{\Delta}{1+\tau}$, the result concerning profit is obvious.

(ii) For any given $r \in [\underline{r}, \overline{r}]$, it is easy to see that $\phi(r)$ defined in (6) increases in x_s, decreases in x_w, and decreases in τ. So the claims follow immediately on the strong lender's interest rate distribution and the weak lender's probability of making an offer upon seeing a good signal. To see the result concerning the weak lender's interest rate distribution, notice that the derivative of

$$\overline{F}_w(r) = \frac{x_s(1-x_w)}{\tau\overline{r} - (1-x_w)} \cdot \frac{\overline{r} - r}{r - \frac{(1-x_s)(1-x_w)}{\tau}}$$

with respect to x_s is proportional to $\tau r - (1 - x_w) \geq 0$. The inequality follows from $\underline{r} = (1-x_w)/\tau$. It is easy to see that $\overline{F}_w(r)$ decreases in both x_w (as the numerator decreases in x_w and the denominator increases in x_w) and τ (as the denominator increases in τ). □

A.5 Proof of Proposition 2

Proof. Result (i) is immediate from Corollary 1. A higher τ induces both lenders to offer lower interest rates (in the sense of first-order stochastic dominance) and also induces the weak lender to be more likely to make offers upon seeing a good signal. This benefits both types of borrowers.

The result concerning the impact of x_s in (ii) is also immediate from Corollary 1. A higher x_s induces both lenders to charge higher interest rates and also induces the weak lender to be less likely to make offers upon seeing a good signal. This harms both types of borrowers.

When x_w increases, we know from Corollary 1 that interest rates go up and the weak lender is more likely to make offers upon seeing a good signal, and so the high-type must become better off. But now the weak lender is less likely to receive a high signal from screening a low-type borrower, and this negatively impacts the low-type borrowers. A straightforward calculation of the derivative of V_l with respect to x_w yields the cut-off result. $\square$

A.6 Proof of Corollary 2

Proof. The result concerning the impact of Δ is immediately from Proposition 2 since for a fixed x_w, increasing Δ is the same as increasing x_s.

The result concerning the impact of the base screening ability x_w is less straightforward. For notational simplicity, in the proof let $x = x_w$ represent the base screening ability. Notice that

$$V_h(x, \Delta, \tau) - \delta = \bar{r}\left(1 - \frac{1-x}{\bar{r}\tau}\right)[1 - \phi(\bar{r})],$$

where $\phi(\bar{r}) = \frac{x+\Delta}{\frac{\tau}{1-x}\bar{r} - 1 + x + \Delta}$. Its derivative with respect to x equals

$$\frac{[\bar{r}\tau - (1-x)][\Delta(1 - x + \bar{r}\tau) + 2\bar{r}\tau x]}{\tau\left[\Delta(1-x) - (1-x)^2 + \bar{r}\tau\right]^2} > 0,$$

where the inequality is from $0 < x < 1$ and Assumption 1 which implies $\bar{r}\tau - (1-x) > 0$. For the low-type borrowers, $V_l(x, \Delta, \tau) = \delta(1 - (x+\Delta)[x + (1-x)\phi(\bar{r})])$ and its derivative with respect to x equals

$$-\frac{[\bar{r}\tau - (1-x)][\Delta(1 - x + \bar{r}\tau) + 2\bar{r}\tau x]}{\left[\Delta(1-x) - (1-x)^2 + \bar{r}\tau\right]^2} < 0.$$

This completes the proof. $\square$

A.7 Proof of Lemma 2

Proof. We prove the result by considering two cases.

(i) Let us first consider the case when both lenders are active in each market segment, which requires $\tau_- \geq 1 - x_f$ and $\tau_+ \geq 1 - x_b$. Define the ϕ function and the lower bound of the interest rate distribution in each market segment as follows:

$$\phi_-(r) = \phi(r; x_f, x_b, \tau_-), \ \ \phi_+(r) = \phi\left(r; x_b, x'_f, \tau_+\right)$$

and

$$\underline{r}_- = \frac{1-x_f}{\tau_-}, \ \underline{r}_+ = \frac{1-x_b}{\tau_+}.$$

When low-type borrowers weakly prefer to sign up, from V_l defined in (10) we know

$$x'_f[x_b + (1-x_b)\phi_+(\bar{r})] \leq x_b[x_f + (1-x_f)\phi_-(\bar{r})].$$

Given $x'_f > x_b > x_f$ and $\phi_+(\bar{r}), \phi_-(\bar{r}) \leq 1$, we deduce that

$$x_b + (1 - x_b)\,\phi_+(\bar{r}) < x_f + (1 - x_f)\,\phi_-(\bar{r}) \leq x_b + (1 - x_b)\,\phi_-(\bar{r}),$$

and so

$$\phi_-(\bar{r}) > \phi_+(\bar{r}). \tag{20}$$

Using the expression for the ϕ function, we have

$$\phi_-(\bar{r}) = \frac{x_b}{\frac{\bar{r}}{\underline{r}_-} - (1 - x_b)} > \phi_+(\bar{r}) = \frac{x'_f}{\frac{\bar{r}}{\underline{r}_+} - (1 - x'_f)} > \frac{x_b}{\frac{\bar{r}}{\underline{r}_+} - (1 - x_b)},$$

where the second inequality used $x'_f > x_b$ and $\frac{\bar{r}}{\underline{r}_+} > 1$. Hence,

$$\underline{r}_- > \underline{r}_+. \tag{21}$$

Then from (20), (21) and V_h defined in (9), we derive

$$V_h\left(x_b, x'_f, \tau_+\right) = (\bar{r} - \underline{r}_+)\,(1 - \phi_+(\bar{r})) > V_h(x_f, x_b, \tau_-) = (\bar{r} - \underline{r}_-)\,(1 - \phi_-(\bar{r})),$$

i.e. the tech-savvy high-type borrowers must strictly prefer to sign up.

(ii) Now consider the case when at least one lender is inactive in at least one market segment. First, suppose $\sigma_h \geq \sigma_l$. Then $\tau_+ \geq \tau$, so both lenders are active in the opt-in market and at least fintech (as the weak lender) is inactive in the opt-out market. Hence, our result holds because high-type borrowers strictly prefer to sign up rather than facing a monopolist bank or no active lender. Second, suppose $\sigma_h < \sigma_l$. Then $\tau_- > \tau$ and so both lenders must be active in the opt-out market and at least the bank is inactive in the opt-in market. If the fintech is also inactive in the opt-in market, our result is of course true; if fintech is active, then the low-type must prefer the opt-out market where there are two active lenders with lower screening abilities. □

A.8 Proof of Proposition 4

Proof. All possible types of equilibrium are summarized in the following table:

	$\sigma_h = 0$	$\sigma_h \in (0,1)$	$\sigma_h = 1$
$\sigma_l = 0$	✓ but trivial	✗	✓
$\sigma_l \in (0,1)$	✗	✗	✓
$\sigma_l = 1$	✗	✗	✓

Using Lemma 2, we can immediately see that it is impossible to have equilibrium with $\sigma_l > 0$ and $\sigma_h < 1$. It is also not hard to rule out the possibility of $\sigma_l = 0$ and $\sigma_h \in (0,1)$. In this hypothetical equilibrium, we must have $\tau_+ = \infty$ and so perfect competition in the opt-in market. Then $V_h(x_b, x'_f, \tau_+) = \bar{r}$, and this must be strictly greater than the surplus from the opt-out market where $\tau_- < \tau$. Therefore, it is impossible for the high-type to randomize, i.e., the hypothetical equilibrium is impossible to exist. It is then clear that in all possible nontrivial equilibria, the tech-savvy high-type borrowers must sign up for open banking for sure, and so $\tau_- \leq \tau_+$.

Conditions for each type of equilibrium. As τ_- may become sufficiently low that at least one lender is inactive in the opt-out market, we first extend the expression for $V_l\left(x_f, x_b, \tilde{r}\right)$ as follows:

$$V_l(x_f, x_b, \tilde{\tau}) = \begin{cases} 1 - x_b \left[x_f + (1 - x_f) \frac{x_b}{\frac{\tilde{\tau}\bar{r}}{1-x_f} - (1-x_b)} \right], & \text{if } \tilde{\tau}\bar{r} \geq 1 - x_f, \\ 1 - x_b, & \text{if } 1 - x_b < \tilde{\tau}\bar{r} < 1 - x_f \\ (1 - x_b)\, m_b, & \text{if } \tilde{\tau}\bar{r} = 1 - x_b, \\ 0, & \text{if } \tilde{\tau}\bar{r} < 1 - x_b. \end{cases} , \tag{22}$$

(We have ignored δ, the size of the non-monetary benefit from getting a loan, as it is irrelevant for our analysis here.) The first case is when both lenders are active as analyzed in section 2.3. Otherwise, fintech exits the opt-out market. In the second case, the bank always makes an offer at the monopoly interest rate $\bar{r}$ upon seeing a good signal (but recall that the low types only care about whether they get a loan). In the third case, the bank makes an offer (at $\bar{r}$) with probability $m_b \in [0, 1]$ upon seeing a good signal (and makes zero profits), where m_b is pinned down in the corresponding equilibrium. In the last case, no lenders are willing to lend and so the surplus is zero.

Recall that, given $\sigma_h = 1$, the updated priors after seeing the sign-up decision are:

$$\tau_-(\sigma_l) = \frac{\rho\tau}{1 - (1 - \rho)\sigma_l} \leq \tau_+(\sigma_l) = \frac{\tau}{\sigma_l}. \tag{23}$$

Note that τ_- increases and τ_+ decreases in σ_l. When $\sigma_l = 0$, τ_- reaches its minimum $\rho\tau$, and τ_+ reaches its maximum ∞; when $\sigma_l = 1$, both are equal to the initial prior τ.

1. For $\sigma_l = \sigma_h = 1$ to be an equilibrium outcome, a necessary condition is $V_l(x_f, x_b, \tau) \leq V_l(x_b, x'_f, \tau)$, i.e., the low-type is willing to sign up. This is also a sufficient condition since Lemma 2 shows that high-type borrowers have higher sign-up incentives, so they must opt in. Meanwhile, as V_l increases in the average credit quality, the above condition also implies $V_l(x_f, x_b, \tau_-) < V_l(x_b, x'_f, \tau_+)$ for any $\sigma_l < 1$, and so the other two types of equilibrium cannot be sustained.

2. For $(\sigma_l \in (0, 1), \sigma_h = 1)$ to be an equilibrium outcome, a necessary condition is

$$V_l(x_f, x_b, \tau_-(\sigma_l)) = V_l(x_b, x'_f, \tau_+(\sigma_l)). \tag{24}$$

This is also a sufficient condition since Lemma 2 implies that the high-type must strictly prefer to sign up in this case. To ensure the existence of this equilibrium, we need to show that (24) has a solution $\sigma_l \in (0,1)$. The stated condition $V_l(x_f, x_b, \tau) > V_l(x_b, x'_f, \tau)$ implies that the left-hand side of (24) is greater than the right-hand side when $\sigma_l = 1$, and the other stated condition $V_l(x_f, x_b, \rho\tau) < V_l(x_b, x'_f, \infty)$ implies that the left-hand side of (24) is smaller when $\sigma_l = 0$. Moreover, the left-hand side $V_l(x_f, x_b, \tau_-(\sigma_l))$ as defined in (22) is continuous and increases in σ_l, while the right-hand side $V_l(x_b, x'_f, \tau_+(\sigma_l))$ is continuous and strictly decreases in σ_l. So there exists a unique solution $\sigma_l \in (0,1)$. Meanwhile, it is clear that the two stated conditions rule out the possibility of the other two types of equilibrium.

3. For $(\sigma_l = 0, \sigma_h = 1)$ to be an equilibrium outcome, a necessary condition is $V_l(x_f, x_b, \rho\tau) \geq V_l(x_b, x'_f, \infty)$, i.e., the low-type does not want to sign up. This is also a sufficient condition, since high-type borrowers strictly prefer to sign up as $V_h(x_f, x_b, \rho\tau) < V_h(x_b, x'_f, \infty) = \overline{r}$. Meanwhile, the above condition also implies $V_l(x_f, x_b, \tau_-) > V_l(x_f, x_b, \rho\tau) \geq V_l(x_b, x'_f, \infty) > V_l(x_b, x'_f, \tau_+)$ for any $\sigma_l > 0$, and so the other two types of equilibrium cannot be sustained.

Solving for $\sigma_l \in (0,1)$ in the semi-separating equilibrium. The exact equation that determines σ_l in (24) depends on how many lenders are active in the opt-out market. Let us first introduce two pieces of notation: let σ'_l solve

$$\tau_-(\sigma'_l)\overline{r} = 1 - x_f,$$

and then in any equilibrium with $(\sigma_l < \sigma'_l, \sigma_h = 1)$ the fintech is in active the opt-out market; let σ''_l solve

$$\tau_-(\sigma''_l)\overline{r} = 1 - x_b,$$

and then in any equilibrium with $(\sigma_l < \sigma''_l, \sigma_h = 1)$, neither lender is active in the opt-out market. $\sigma'_l \in (0,1)$ is well defined if $\rho\tau\overline{r} < 1 - x_f$, and $\sigma''_l \in (0,1)$ is well defined if $\rho\tau\overline{r} < 1 - x_b$, and $\sigma''_l < \sigma'_l$ in the latter case. More explicitly, we have

$$\sigma'_l = \left(1 - \frac{\rho\tau\overline{r}}{1 - x_f}\right)\frac{1}{1-\rho};\ \sigma''_l = \left(1 - \frac{\rho\tau\overline{r}}{1 - x_b}\right)\frac{1}{1-\rho}.$$

We need to deal with three cases separately:

(i) When $\rho\tau\overline{r} \geq 1 - x_f$, even if τ_- reaches its minimum $\rho\tau$, both lenders will be active in the opt-out market, and so $V_l(x_f, x_b, \tau_-)$ takes the standard form as in the first case of (22). Then (24) becomes

$$x_b[x_f + (1 - x_f)\frac{x_b}{\frac{\tau_-(\sigma_l)}{1-x_f}\overline{r} - 1 + x_b}] = x'_f[x_b + (1 - x_b)\frac{x'_f}{\frac{\tau_+(\sigma_l)}{1-x_b}\overline{r} - 1 + x'_f}], \tag{25}$$

where $\tau_-(\sigma_l)$ and $\tau_+(\sigma_+)$ are defined in (23).

(ii) When $1 - x_b < \rho\tau\overline{r} < 1 - x_f$, depending on whether equilibrium $\sigma_l \geq \sigma'_l$, fintech may participate in or exit the opt-out segment in the semi-separating equilibrium. If $V_l(x_f, x_b, \tau_-(\sigma_l')) > V_l(x_b, x_f', \tau_+(\sigma_l'))$, then in equilibrium $\sigma_l < \sigma_l'$ and fintech becomes inactive in opt-out segment, and thus σ_l solves $1 - x_b = V_l(x_b, x_f', \tau_+(\sigma_l))$, or more explicitly,

$$x_b = x_f'[x_b + (1 - x_b)\frac{x_f'}{\frac{\tau_+(\sigma_l)}{1-x_b}\overline{r} - 1 + x_f'}]. \tag{26}$$

Otherwise, if $V_l(x_f, x_b, \tau_-(\sigma_l')) \leq V_l(x_b, x_f', \tau_+(\sigma_l'))$, then in equilibrium $\sigma_l \geq \sigma_l'$ and both lenders are active in the opt-out market, and σ_l solves the same equation (25) as in case (i). Also notice that in this case, $V_l(x_f, x_b, \rho\tau) = 1 - x_b < V_l(x_b, x_f', \infty) = 1 - x_b x_f'$, and so it is impossible to have the third type of separating equilibrium.

(iii) When $\rho\tau\overline{r} \leq 1 - x_b$, depending on the relationship between the equilibrium σ_l, σ_l', and σ_l'', the fintech may exit and the bank may randomly pass upon seeing good signal in the opt-out segment. Correspondingly, $V_l(x_f, x_b, \tau_-)$ could take the first three forms as in (22). If $V_l(x_f, x_b, \tau_-(\sigma_l')) \leq V_l(x_b, x_f', \tau_+(\sigma_l'))$, then the equilibrium $\sigma_l \geq \sigma_l'$, and both lenders are active in the opt-out segment, so σ_l solves (25). If $V_l(x_f, x_b, \tau_-(\sigma_l'')) < V_l(x_b, x_f', \tau_+(\sigma_l''))$ but $V_l(x_f, x_b, \tau_-(\sigma_l')) > V_l(x_b, x_f', \tau_+(\sigma_l'))$, then the equilibrium $\sigma_l \in (\sigma_l'', \sigma_l')$, the fintech becomes inactive in the opt-out segment while the bank makes positive profits, so σ_l solves (26). If $V_l(x_f, x_b, \tau_-(\sigma_l'' + \epsilon)) > V_l(x_b, x_f', \tau_+(\sigma_l'' + \epsilon))$ for small $\epsilon > 0$, then the equilibrium $\sigma_l = \sigma_l''$, and still only the bank is active in the opt-out segment but it makes zero profit and randomly drops out upon seeing good signal. □

A.9 Proof of Corollary 3

Proof. 1. The results have been explained in the main text.

2. We only need to show that there is a nonempty set of primitive parameters such that (14) and (15) hold. First, by continuity we can focus on the case of $x_b = x_f$. (Our argument below continues to work when x_b and x_f are sufficiently close to each other.)

Second, given V_h decreases in the strong lender's screening ability and $x_f' > x_b$, the second inequality in (14) must hold if τ_+ is sufficiently close to τ. This is the case if σ_l is sufficiently close to 1.

Third, we choose τ_- such that $\tau_-\overline{r} = 1 - x_f$. Given our assumption $\tau\overline{r} > 1 - x_f$, we must have $\tau_- < \tau$. When $\sigma_h = 1$, we have

$$\tau_- = \tau \cdot \frac{\rho}{1 - (1 - \rho)\,\sigma_l}.$$

Then for any $\tau_- < \tau$ and $\sigma_l \in (0, 1)$, we must be able to find a $\rho \in (0, 1)$ that solves the above equation. (By continuity, this step also works when τ_- is such that $\tau_-\overline{r}$ is slightly above $1 - x_f$.)

Finally, we need (15) to hold for some parameters. The remaining parameter we can choose is

x'_f. When $\tau_-\overline{r} = 1 - x_f$, one can check that $\frac{V_l(x_f, x_b, \tau_-)}{\delta} = 1 - x_b$. Then (15) requires

$$x_b = x'_f \left(x_b + (1 - x_b) \frac{x'_f}{\frac{\overline{r}\tau_+}{1 - x_b} - 1 + x'_f} \right). \tag{27}$$

Notice that when $\tau_+ = \tau$, given (1), there exists $\varepsilon > 0$ such that the above equation has a solution $x'_f \in (x_b + \varepsilon, 1)$. (To see this, the right-hand side of (27) exceeds x_b when $x'_f = 1$, and given that $\overline{r}\tau > 1 - x_b$, it is less than x_b for some $\varepsilon > 0$ if $x'_f = x_b + \varepsilon$.) The same argument works if τ_+ is sufficiently close to τ. That is, for a $\tau_+ = \frac{\tau}{\sigma_l} \approx \tau$ (or $\sigma_l \approx 1$) chosen in the second step, the above equation has a solution x'_f bounded away from x_b so that (15) holds. This completes the proof. (Note that the parameters identified by this argument ensure that both lenders are active even in the opt-out market.)

3. We now focus on the case when all borrowers suffer due to open banking and both lenders are active in the opt-out market. (The proof for result 2 has shown that such an outcome can arise for some parameters.) Before open banking, the bank earns $\pi_b^0 = \frac{\Delta}{1+\tau}$ and the fintech earns $\pi_f^0 = 0$. After open banking, let n_+ and n_- be the measure of consumers who sign up and who do not, respectively. (They satisfy $n_+ + n_- = 1$.) Notice that we must have $n_+ (1 - \theta_+) + n_- (1 - \theta_-) = 1 - \theta$, where θ_+ and θ_- are respectively the fraction of high-type borrowers in each market segment. This is equivalent to

$$\frac{n_+}{1 + \tau_+} + \frac{n_-}{1 + \tau_-} = \frac{1}{1 + \tau}. \tag{28}$$

In the opt-in market, the two lenders' profits are respectively

$$\pi_b^+ = 0, \ \pi_f^+ = n_+ \frac{\Delta'}{1 + \tau_+}.$$

In the opt-out market, the two lenders' profits are respectively

$$\pi_b^- = n_- \frac{\Delta}{1 + \tau_-}, \ \pi_f^- = 0.$$

It is clear that the fintech earns a higher profit than before, while the bank's profit drops as

$$\pi_b^0 = \frac{\Delta}{1 + \tau} > \pi_b^+ + \pi_b^- = n_- \frac{\Delta}{1 + \tau_-},$$

where the inequality used (28).

Industry profit goes up if and only if

$$\pi_f^+ + \pi_b^- = n_+ \frac{\Delta'}{1 + \tau_+} + n_- \frac{\Delta}{1 + \tau_-} > \pi_b^0 = \frac{\Delta}{1 + \tau}.$$

Given (28), this is the case if $\Delta' > \Delta$, which must be true in our equilibrium where the high-type borrowers who sign up suffer due to open banking. (This is because from Corollary 2, we know that V_h increases in base screening ability and average credit quality but decreases in the ability gap. In the sign-up market segment, the base ability improves from x_f to x_b and the average credit quality improves from τ and τ_+, and so the high-type borrowers become worse off only if $\Delta' > \Delta$.)

The result concerning market efficiency follows from the same argument as in the case of mandatory sign-up. □

A.10 Proof of Proposition ??

Proof. Similar results as in the baseline competition apply here: lenders randomize over common support $\left[\underline{r}^{\xi}, \overline{r}\right]$, and at most one of them can have a mass point at the top $r = \overline{r}$.

The case of $\xi < \phi(\overline{r})$:

From Equation (**??**), if $\xi < \phi(\overline{r})$, the fintech's profit in the ξ-event is dominated by the winner's curse in the non–ξ-event. Hence, similar as in Proposition 1, one lender randomly drops out and the other has a mass point at the top. The fintech must randomly drops out, or else $\pi_f^{\xi} > \pi_b^{\xi} = 0$ and $(1-\xi)\,\pi_f^{\xi} > \pi_b^{\xi}$, which further implies $p_{LH} < p_{HL}$, which is a contradiction.

To characterize the equilibrium, recall that $\phi(r) = \frac{x_b}{\frac{\tau}{1-x_f}r-(1-x_b)}$, and then the fintech's indifference condition (**??**) yields:

$$\overline{F}_b^{\xi}(r) = \frac{\phi(r) - \xi}{1-\xi} = \frac{1}{1-\xi}\left(\frac{x_b}{\frac{\tau}{1-x_f}r - (1-x_b)} - \xi\right),$$

which is well defined when $\xi \le \phi(\overline{r}) < 1$; F_b^{ξ} has a mass point at $r = \overline{r}$ with size

$$\lambda_b^{\xi} = \frac{\phi(\overline{r}) - \xi}{1-\xi}.$$

The fintech has the same strategy as in the baseline (the bank has the same indifference condition **??**): upon seeing a good signal, it makes an offer with probability $m_f^{\xi} = 1 - \phi(\overline{r})$, and the offer randomizes over $\left[\underline{r}^{\xi}, \overline{r}\right]$ according to

$$\overline{F}_f^{\xi}(r) = \frac{\phi(r) - \phi(\overline{r})}{1-\phi(\overline{r})}.$$

As for borrower surplus, the high-type borrowers care about the expected interest rate, so

$$V_h^{\xi}(\tau) = \left(1 - \xi + \xi m_f^{\xi}\right)\overline{r} - \underbrace{\left\{(1-\xi)\cdot\left[(1-m_f^{\xi})\mathbb{E}[r_b^{\xi}] + m_f^{\xi}\mathbb{E}[\min\{r_b^{\xi}, r_f^{\xi}\}]\right] + \xi\cdot m_f^{\xi}\cdot\mathbb{E}[r_f^{\xi}]\right\}}_{\text{expected interest rate}}$$

where the second term in the curly bracket corresponds to the ξ-event in which there is only one lender. Plugging in $\overline{F}_j^{\xi}(r)$ and m_f^{ξ} yields $V_h^{\xi}(\tau) = V_h(\tau)$. Low-type borrowers only care about the probability of receiving a loan, so

$$V_l^{\xi}(\tau) = (1-\xi) V_l(x_f, x_b, \tau) + \xi (1 - x_f)(1 - \phi(\overline{r})) \delta.$$

In the $1-\xi$ event, the equilibrium differs from baseline equilibrium only in bank pricing $\overline{F}_b^{\xi}(r)$, and thus the low-type have the same surplus $V_l(x_f, x_b, \tau)$; in the ξ-event, the fintech is the only lender, and the borrower receives the loan when (wrongly) screened as H (probability $1-x_f$) and the fintech does make the offer (probability $m_f^{\xi} = 1 - \phi(\overline{r})$).

The case of $\xi = \phi(\overline{r})$:

By continuity, there exists an equilibrium of the same structure as in the case of $\xi < \phi(\overline{r})$. In this equilibrium, the size of the bank's mass point at $\overline{r}$ shrinks to $\lambda_b^{\xi} = 0$ exactly, so the fintech may have a mass point at $\overline{r}$. Specifically, there exists a continuum of equilibria indexed by $m_f^{\xi} \in [1-\phi(\overline{r}), 1]$ that satisfy $1 - m_f^{\xi} + m_f^{\xi}\lambda_f^{\xi} = \phi(\overline{r})$. Accordingly, $\lambda_f^{\xi} = 1 - \frac{1-\phi(\overline{r})}{m_f^{\xi}}$, and $\overline{F}_f^{\xi}(r) = 1 - \frac{1-\phi(r)}{m_f^{\xi}}$, and the other equilibrium variables are the same as in the case of $\xi < \phi(\overline{r})$. The exact m_f^{ξ} affects the probability of a loan and hence the low type's surplus $V_l^{\xi}(\tau) = \delta\left\{1 - x_b\left[x_f + (1-x_f)\left(1 - m_f^{\xi}\right)\right]\right\}$, while the high-type still earn $V_h^{\xi}(\tau) = V_h(\tau)$.

The case of $\xi > \phi(\overline{r})$:

Similar to Varian (1980), the unique equilibrium is a mixed-strategy on common support $\left[\underline{r}^{\xi}, \overline{r}\right]$. Equation (**??**) shows that when $\xi > \phi(\overline{r})$, the fintech makes positive profit (one feasible strategy is to always offer $r = \overline{r}$ upon seeing a good signal). So both lenders have positive profits and always make an offer upon seeing a good signal, $m_j^{\xi} = 1$ for $j \in \{b, f\}$.[34]

The fintech's indifference condition is

$$r \in \left(\underline{r}^{\xi}, \overline{r}\right): \ \pi_f^{\xi} = p_{HH}\left[\xi + (1-\xi)\overline{F}_b^{\xi}(r)\right]\left[\mu_{HH}(r+1) - 1\right] - p_{LH}. \tag{29}$$

Evaluating (29) at $r = \overline{r}$ yields the fintech's profit

$$\pi_f^{\xi} = \xi \cdot \frac{\tau\overline{r} - (1-x_f)}{1+\tau} - (1-\xi) \cdot \frac{x_b(1-x_f)}{1+\tau}, \tag{30}$$

which allows us to solve for $\underline{r}^{\xi}$ (as the fintech earns π_f^{ξ} at $\underline{r}^{\xi}$ as well):

$$\underline{r}^{\xi} = \xi\overline{r} + (1-\xi)\frac{(1-x_b)(1-x_f)}{\tau} > \underline{r}. \tag{31}$$

[34]The traditional bank must also make positive profit $\pi_b^{\xi} > 0$ due to better screening ability. To see this, consider when a lender posts $r = \underline{r}^{\xi}$ and gets to serve all borrowers tested with HH. Then adjusting for market size, the traditional bank suffers due to a less serious winner's curse.

Lastly, the fintech is indifferent across $r \in \left[\underline{r}^{\xi}, \overline{r}\right)$, implying

$$\overline{F}_b^{\xi}(r) = \frac{\xi}{1-\xi} \cdot \frac{\phi(r) - \phi(\overline{r})}{\phi(\overline{r})}.$$

The bank's indifference condition is

$$r \in \left(\underline{r}^{\xi}, \overline{r}\right) : \ \pi_b^{\xi} = (1-\xi)\left\{p_{HH}\overline{F}_f^{\xi}(r)\left[\mu_{HH}(r+1) - 1\right] - p_{HL}\right\}. \tag{32}$$

Using this condition at $r = \underline{r}^{\xi}$, we have bank profit

$$r = \underline{r}^{\xi} : \ \pi_b^{\xi} = (1-\xi)\, p_{LH}\left(\frac{\xi}{\phi(\overline{r})} - \frac{p_{HL}}{p_{LH}}\right);$$

the bank's indifference condition across $r \in \left[\underline{r}^{\xi}, \overline{r}\right)$ pins down the fintech's strategy

$$\overline{F}_f^{\xi}(r) = \frac{\xi\phi(r)}{\phi(\overline{r})},$$

with the mass point $\lambda_f = \xi$. Note that $\overline{F}_f^{\xi}(r)$ strictly increases in ξ.

As for borrowers' surplus, a high-type borrower always receives a loan and cares about the expected interest rate,

$$V_h^{\xi}(\tau) = \overline{r} - \left[(1-\xi)\,\mathbb{E}\left[\min\left\{r_b^{\xi}, r_f^{\xi}\right\}\right] + \xi\mathbb{E}\left[r_f^{\xi}\right]\right] = (1-\xi)^2\left[\overline{r} - \frac{(1-x_b)(1-x_f)}{\tau}\right].$$

A low-type borrower receives a loan when in the ξ-event she is screened as H with the fintech, or when otherwise she is screened as H with at least one of the lenders,

$$V_l^{\xi}(\tau) = \delta\left[\xi(1-x_f) + (1-\xi)(1-x_b x_f)\right].$$

In addition, we show that high types are worse off, i.e., $V_h^{\xi}(\tau) < V_h(\tau)$ when $\xi > \phi(\overline{r})$. Recall that the expected interest rate in the baseline is $m_f\mathbb{E}\left[\min\left\{r_b, r_f\right\}\right] + (1-m_f)\,\mathbb{E}\left[r_b\right] = \underline{r} + \int_{\underline{r}}^{\overline{r}} \phi^2(r)\, dr$, and the expected interest rate here is

$$\begin{aligned}
(1-\xi)\,\mathbb{E}\left[\min\left\{r_b^{\xi}, r_f^{\xi}\right\}\right] + \xi\mathbb{E}\left[r_f^{\xi}\right] &= \underline{r}^{\xi} + \frac{\xi^2}{\phi^2(\overline{r})}\int_{\underline{r}^{\xi}}^{\overline{r}} \phi^2(r)\, dr \\
&= \underline{r} + \underbrace{\int_{\underline{r}}^{\underline{r}^{\xi}} dr}_{\underline{r}^{\xi} > \underline{r}} + \underbrace{\frac{\xi^2}{\phi^2(\overline{r})}}_{\geq 1}\int_{\underline{r}^{\xi}}^{\overline{r}} \phi^2(r)\, dr \\
&> \underline{r} + \int_{\underline{r}}^{\underline{r}^{\xi}} \phi^2(r)\, dr + \int_{\underline{r}^{\xi}}^{\overline{r}} \phi^2(r)\, dr = \underline{r} + \int_{\underline{r}}^{\overline{r}} \phi^2(r)\, dr
\end{aligned}$$

Note that there is a discontinuous downward jump in $V_h^\xi(\tau)$ at the threshold $\xi = \phi(\bar{r})$: for a smaller ξ the ξ-event does not affect borrower surplus but a larger ξ makes her worse off. □

A.11 Proof of Proposition ??

Proof. 1. When $\xi \leq \phi(\bar{r})$, it is straightforward to check that $V_h^{\xi,OB}(\tau) < V_h^\xi(\tau)$ in (**??**) and $V_l^{\xi,OB}(\tau) > V_l^\xi(\tau)$ from the fintech's offering probability in the ξ-event. When $\xi > \phi(\bar{r})$, the low-type suffer due to open banking because by comparing (**??**) and (**??**), we have

$$V_l^\xi = \delta(1-\xi)(1-x_b x_f) + \delta\xi(1-x_f) > (1-\xi)V_l(\tau) + \delta\xi(1-x_f) = V_l^{\xi,OB}(\tau), \qquad (33)$$

where the inequality holds as $\delta(1-x_b x_f)$ is greater than $V_l(\tau)$ in (10). (The equality will hold if $\tau \to \infty$.)[35] The high-type suffer due to open banking if

$$V_h^\xi(\tau) = (1-\xi)^2\left[\bar{r} - \frac{(1-x_b)(1-x_f)}{\tau}\right] > (1-\xi)V_h(\tau) = V_l^{\xi,OB}(\tau),$$

which is equivalent to

$$(1-\xi)(\bar{r} - \underline{r} + x_b \underline{r}) > V_h(\tau) = (\bar{r} - \underline{r})(1-\phi(\bar{r})).$$

This holds if and only if ξ is below some threshold $\hat{\xi} \in (\phi(\bar{r}), 1)$.

2. When $\xi \leq \phi(\bar{r})$, the fintech earns a zero profit before open banking but a positive profit after, and the bank makes the same profit in either case. When $\xi > \phi(\bar{r})$, from (**??**) and (30) it is immediate to see that the fintech benefits from open banking; while the bank suffers as

$$\pi_b^\xi = (1-\xi)\left\{p_{HH}\left[\mu_{HH}\left(\underline{r}^\xi + 1\right) - 1\right] - p_{HL}\right\} > \pi_b^{\xi,OB} = (1-\xi)\left\{p_{HH}\left[\mu_{HH}(\underline{r}+1) - 1\right] - p_{HL}\right\},$$

where $\underline{r}^\xi > \underline{r}$ as shown in Proposition **??**. □

A.12 Proof of Proposition ??

This proof is provided in the Online Appendix C.3.

[35]In the knife edge case, open banking may hurt or benefit low-type depending on the equilibrium $m_f^\xi \in [1-\phi(\bar{r}), 1]$.

A.13 Proof of Proposition ??

Proof. Recall that θ_+, θ_- are respectively the average quality of opt-in and opt-out borrowers. Naturally $p(\xi)\theta_+ + (1-p(\xi))\theta_- = \theta$, and thus $p(\xi) = \frac{\theta-\theta_-}{\theta_+-\theta_-}$ decreases in both θ_+ and θ_-. From Proof A.12, there exists a $\tilde{\xi} \in (\phi(\overline{r};\tau), \phi(\overline{r};\rho\tau))$ such that when $\xi < \tilde{\xi}$, the high-type are indifferent about signing up; in this case, τ_+ decreases in ξ to balance the deterioration of τ_-. Hence, $p(\xi)$ increases in ξ in this range. When $\xi \geq \tilde{\xi}$, the sign-up population is smaller in a hypothetical equilibrium where the high-type are indifferent than when the high-type strictly prefer to sign up. To see this, as $\phi\left(\overline{r}; \tau_- = \tau\frac{\rho+(1-\rho)(1-\sigma_h)}{\rho+(1-\rho)(1-\sigma_l)}\right) = \xi$, σ_l must be smaller if $\sigma_h < 1$ than when $\sigma_h = 1$. When $\sigma_h = 1$, we have $\sigma_l = \frac{1-\frac{\tau}{\tau_-}\rho}{1-\rho}$, under which $p(\xi) \equiv (1-\rho)[\theta + (1-\theta)\sigma_l]$ decreases in ξ. Therefore, $p(\xi)$ is single-peaked at $\tilde{\xi}$.

Then we discuss the welfare implications for $\xi \in \left[\phi(\overline{r};\tau), \tilde{\xi}\right]$. First, since tech savvy borrowers of both credit type are indifferent to sign up and have the same surplus as non--tech-savvy borrowers. Hence, it suffices to discuss how open banking affects the non–tech-savvy borrowers. We argue that the high-type lose,

$$\Delta V_h^{\xi,OB} = \underbrace{V_h(\tau_-)}_{V_{h,\rho}^{\xi,OB}} - \underbrace{(1-\xi)^2\left[\overline{r} - \frac{(1-x_b)(1-x_f)}{\tau}\right]}_{V_{h,\rho}^{\xi}(\cdot)} = \frac{(1-\xi)^2}{\tau}\frac{(1-x_b)(1-x_f)x_b}{x_b+\xi(1-x_b)}\left[1 - \frac{\xi}{\phi(\overline{r};\tau)}\right] < 0.$$

Note that before open banking, lenders always make loans upon receiving H signal when $\xi \geq \phi(\overline{r};\tau)$, so low-type borrowers are hurt by open banking: $\Delta V_l^{\xi,OB} < 0$. Therefore, all borrowers are hurt by open banking when $\xi \in \left[\phi(\overline{r};\tau), \tilde{\xi}\right]$ even if they voluntarily choose whether or not to sign up.

Now we study firm profits. In the region of $\phi(\overline{r};\tau) \leq \xi \leq \phi(\overline{r};\rho\tau)$, we show that open banking hurts the bank while benefits the fintech. To see this, the profits of two lenders after open banking are

$$\pi_b^{\xi,OB} = \pi_{b+}^{\xi,OB} + \pi_{b-}^{\xi,OB} = \underbrace{n_+(1-\xi)\frac{x_b-x_f}{1+\tau_+}}_{=\pi_{b+}^{\xi,OB}} + \underbrace{n_-(1-\xi)\frac{x_b-x_f}{1+\tau_-}}_{=\pi_{f-}^{\xi,OB}} = (1-\xi)\frac{x_b-x_f}{1+\tau},$$

$$\pi_f^{\xi,OB} = \pi_{f+}^{\xi,OB} + \underbrace{\pi_{f-}^{\xi,OB}}_{=0} = \xi\left[\theta(1-\rho)\sigma_h\overline{r} - (1-\theta)(1-\rho)\sigma_l(1-x_f)\right];$$

while their profits before open banking are

$$\pi_b^{\xi} = (1-\xi)\left[\xi\frac{\overline{r}\tau}{1+\tau} - \xi\frac{1-x_b}{1+\tau} - (1-\xi)\frac{(1-x_b)x_f}{1+\tau}\right],$$

$$\pi_f^{\xi} = \xi\theta\overline{r} - \xi(1-\theta)(1-x_f) - (1-\xi)(1-\theta)x_b(1-x_f).$$

We hence have that

$$\Delta\pi_b^{\xi,OB} \equiv \pi_b^{\xi,OB} - \pi_b^{\xi} = \frac{(1-\xi)(1-x_f)\,x_b}{1+\tau}\left(1 - \frac{\xi}{\phi(\overline{r};\tau)}\right) < 0;$$
$$\Delta\pi_f^{\xi,OB} = \pi_f^{\xi,OB} - \pi_f^{\xi} = \frac{\xi(1-x_f)}{1+\tau}(1-\rho)\,\sigma_l\left(\frac{\overline{r}\tau_-}{1-x_f} - 1\right) > 0.$$

The change in industry profits $\Delta\pi_b^{\xi,OB} + \Delta\pi_f^{\xi,OB}$ is less straightforward, and hence we provide the comparative analysis in the Online Appendix C. □

B Open Banking: A Brief Overview

In this brief overview of open banking, we outline the underlying Application Programming Interfaces (APIs) technology and its connection to fintech, the current status of open banking in practice, and its core difference from credit reports used by traditional banking. Given the focus of paper, we organize this section with the theme of credit market development and competition.

Open Banking: Fintech and Banking Disruption As we have mentioned in Introduction, open banking is a series of reforms in Europe related to how banks deal with customers' financial information, called for by the Competition and Markets Authority (CMA), the competition watchdog in the U.K.. Together with PSD2, all U.K.-regulated banks have to let customers share their financial data—e.g., regular payments, credit card expenses, or savings statements—with authorized providers, including fintech companies, as long as customers give permission. Besides other data security measures, the CMA sets up the open banking standard for APIs, which are intelligent conduits that allow for secure data sharing among financial institutions in a controlled yet seamless fashion. With APIs, customers can connect their bank accounts to an app that can analyze their spending, recommend new financial products (e.g., credit cards), or sign up with a provider to display all of their accounts with multiple banks in one place so they have a better overview of their finances.[36]

[36] In practice, there are two main ways, screen-scraping and APIs, by which third parties can access customers' data. In screen-scraping, by giving providers "read-only" access to your online banking, you are giving it your login details and letting it pretend to be you. Screen-scraping is not as safe as API, where you can give your financial institution the rights to share your financial data with a third party, via a secure token generated by the financial institution. The token does not contain your login credentials and hence is much more secure than the screen-scraping method; what is more, because programming facilitates customer control, APIs hence can allow access to only specific assets rather than your entire financial profile. Investment management firms were among the early power users of APIs, importing data on rates, fund performance, trade clearing and more from third parties. Nowadays, APIs are already widely used by big-tech companies (e.g., Uber uses Google Maps' API so it can work out where you and your driver are) and gaining popularity in the banking industry (e.g., Zelle allows depositors in the U.S. to transfer money among their bank accounts within minutes via API). For more discussions on API and its legal issues, see "Open

Open banking truly came into effect in September 2019 with the full enforcement of PSD2, which mandates that banks open their data to third parties, and also offer protections around customer data. According to the two-part series (one and two) titled "Open Banking Is Now Essential Banking: A New Decade's Global Pressures and Best Responses" by Forbes in early 2021, open banking "is disruptive, global and growing at a breakneck pace," featuring "a disruptive model that asks basic questions about who creates and controls banking services." According to Allied Market Research, the open banking market, accelerated by the pandemic, is growing at 24.4% annually and has been part of an inevitable control shift in the financial sector.

There are many players in this nascent industry, where fintechs and traditional banks interact closely. The first segment consists of technology companies who are open-banking enablers (e.g., Plaid) who specialize in APIs and other solutions to support traditional banks. Financial data aggregation companies (e.g., Mint), sit in the second segment, in which financial institutions create partnerships with fintechs to get access to traditional banks' financial data via APIs, so that consumers can manage their personal finances from a single dashboard.

Taking one step beyond "information aggregators," the third segment "lending marketplaces" aims to provide a platform where borrowers and lenders exchange digital information for more efficient loan/financing decisions. Similar to the quote by Dan Kettle at *Pheabs* mentioned in the Introduction, *MarketFinance* in the U.K., which specializes in invoice financing, said[37]

> For customers who want funds even faster, we're taking this further by introducing our Open Banking feature. When a customer chooses to connect their business account to their MarketFinance account, they allow us to view their transactions. This technology gives us the ability to make more informed decisions about their customer base and business activity. So we can verify the activity faster and trust a higher invoice value without spending time checking it out first.

While incumbents still hold the keys to the vault in terms of rich transaction data as well as trusted client relationships, banks often view the opening of these data flows as more of a threat than an opportunity.[38] This is especially true for fintech challengers that offer competing services and have gained valuable new (e.g., alternative unstructured) data via their modern customer relationships. Our theory highlights that a perverse effect of open banking in which all borrowers might be hurt is more likely to arise, even with voluntary sign-ups.

Banking, APIs, and Liability Issues" by Rich Zukowsky (2019).

[37]See link.

[38]Of course, major traditional banks are also adapting themselves to this new technology. For example, Bank of America is developing open banking platforms, HSBC is nurturing fintechs, and JPMorgan is employing the banking-as-a-service model. For more details, see the two-part series by Forbes in early 2021 mentioned in Introduction.

Open Banking: Where Are We Now? Open banking had a slow start since the creation of the Open Banking Implementation Entity (OBIE) by the CMA in the U.K. in 2016. However, open banking adoptions accelerated in a dramatic way after the COVID-19 pandemic. According to the OBIE's latest annual report, over 3 million customers have connected their accounts to trusted third parties by February 2021, up from 1 million in January 2020. In another related report that focuses on how small businesses in the U.K., the OBIE together with Ipsos MORI found that 50% of surveyed small businesses now use open banking providers as of December 2020. What is more, 18% of surveyed small businesses took alternative credit (i.e., not from traditional bank), and "*open banking data is increasingly being used to offer credit as it allows lending providers to more accurately assess creditworthy borrowers and shape funding solutions specific to their needs.*"

Open banking is no longer just a European initiative, as more and more areas are becoming open banking friendly. Hong Kong has already developed its own open banking regulation "Open API" in 2018, and countries like U.S. and China are in the process of building their own open banking ecosystems. For concrete examples, see Ultra FICO and the recent development of REACh in the U.S. as mentioned in the Introduction.

C Online Appendix

C.1 Properties of Mixed-Strategy Equilibria

Here we show that in our baseline model any mixed-strategy equilibrium is well behaved.

Lemma 3. *In any mixed-strategy equilibrium, the two lenders' interest rate distributions have the following properties:*

1. *they share the same lower bound $\underline{r} > 0$ and the same upper bound $\overline{r}$ in their supports;*

2. *they have no gaps in their supports;*

3. *one of them can have a mass point at $\overline{r}$ and otherwise they have no mass points.*

Proof. Here we show the properties of a mixed-strategy equilibrium. (i) For the lower bound result, suppose in contrast that, say, $\underline{r}_w < \underline{r}_s$, i.e. F_w has a smaller lower bound than F_s. Then for the weak lender, offering $r \in (\underline{r}_w, \underline{r}_s)$ is always more profitable than offering $\underline{r}_w$ since both lead to the same demand. This contradicts $\underline{r}_w$ being in the support. For the upper bound result, suppose first $\max\{\overline{r}_w, \overline{r}_s\} < \overline{r}$. If $\overline{r}_w \neq \overline{r}_s$, then for the lender with the higher upper bound, offering an interest rate slightly above its upper bound will be a profitable deviation. If $\overline{r}_w = \overline{r}_s$, since it is impossible that both distributions have a mass point at this upper bound, at least one lender will have an incentive to slightly raise its interest rate without losing any demand. Now suppose, say, $\overline{r}_w < \overline{r}$ and $\overline{r}_s = \overline{r}$. Then the support of F_s would have a gap in $(\overline{r}_w, \overline{r})$ since any interest rate in this interval is dominated by $\overline{r}$. But this is impossible in equilibrium since for at least one lender offering an interest rate slightly above $\overline{r}_w$ would be a profitable deviation. This proves $\overline{r}_w = \overline{r}_s = \overline{r}$.

(ii) Suppose that, say, the support of F_s has a gap $(r_1, r_2) \subset [\underline{r}, \overline{r}]$. Then F_w should have no weight in this interval either as any $r \in (r_1, r_2)$ will lead to the same demand for the weak lender and so a higher r will be more profitable. If neither distribution has a mass point at r_1, unilaterally offering $r \in (r_1, r_2)$ will be a profitable deviation for either lender. If one distribution, say, F_s has a mass point at r_1, unilaterally offering $r \in (r_1, r_2)$ will be a profitable deviation for the strong lender. It is impossible that both distributions have a mass point at r_1.

(iii) Suppose first that one distribution, say, F_s has a mass point at $r = \underline{r}$. Then it will be a profitable deviation for the weak lender to offer an interest rate slightly below $\underline{r}$. Suppose then that F_s has a mass point at $\tilde{r} \in (\underline{r}, \overline{r})$. Then for the weak lender, an interest rate just slightly below $\tilde{r}$ should be more profitable than any interest rate in $[\tilde{r}, \tilde{r}+\varepsilon]$ for some $0 < \varepsilon < \overline{r} - \tilde{r}$. In other words, the support of F_w must have a gap in this interval. This, however, is impossible as we have shown in (ii). Finally it is impossible that both distributions have a mass point at $\overline{r}$. □

C.2 Two Fintech Lenders

C.2.1 Asymmetric Fintechs

Lemma 4. *Suppose that there are lenders with asymmetric screening abilities $x_s > x_m > x_w$ (subscripts denote the strong, medium, and weak lender respectively), then there are only two active lenders.*

Proof. Lender profit (as evaluated at the lowest interest rate $\underline{r}$) is[39]

$$\pi_j = p_{HHH}\left[\mu_{HHH}\left(1+\underline{r}\right)-1\right] - \mathbb{P}\left(S_j = H, S_{-j} \neq HH\right) = \theta\underline{r} - (1-\theta)\left(1-x_j\right).$$

Hence,

$$\pi_s > \pi_m > \pi_w.$$

If all lenders are present with positive probability, then $\pi_w \geq 0$. It follows that $\pi_s > \pi_m > 0$, and the medium and strong lenders never withdraw upon good signal, i.e., $m_m = m_s = 1$. For them to be indifferent at $r = \overline{r}$, both must have a mass point at the top. Take the strong lender as an example (with $\frac{1}{2}$ as the tie-breaking rule),

$$\pi_s\left(\overline{r}\right) = p_{HHH}\left(1-m_w+m_w\lambda_w\right)\lambda_m \cdot \frac{1}{2}\left[\mu_{HHH}\left(1+\overline{r}\right)-1\right] - p_{HLH} - p_{HHL} - p_{HLL} > 0 \Rightarrow \lambda_m > 0.$$

Contradiction. Hence, $\pi_w < 0$ and the weak lender exits the market. □

C.2.2 Symmetric Fintechs

Now consider the case where there is one bank, and two fintechs with symmetric screening abilities both before and after open banking. Consistent with our two-lender discussion, we consider

$$x_f' > x_b > x_f.$$

Before open banking, there exists an equilibrium in which fintechs make zero profits and the bank makes positive profit

$$\pi_b > 0 = \pi_f.$$

After open banking, the bank leaves the market, and two fintechs make zero profit

$$\pi_{f'} = 0.$$

[39]We focus on the well-behaved equilibria with smooth pricing strategies over common interval support.

We make the following assumptions to further simplify the analysis. To eliminate the effects of screening efficiency and focus on the number of lenders, suppose

$$x_f \nearrow x_b \nearrow x_{f'} \equiv x. \tag{34}$$

We assume that $\delta \to 0$: this does not affect the equilibrium that arises, and simplifies calculating the high-type surplus.

Competition Equilibrium Characterize the competitive equilibrium before open banking. Let $S_b S_f S_f$ denote the signal sequence. The bank's indifference condition is given by

$$\pi_b(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right]^2}_{\text{winning both competitors}} \left[\mu_{HHH}(1+r) - 1\right] \tag{35}$$

$$- 2 \underbrace{p_{HHL}}_{b \text{ and one } f \text{ make mistakes}} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right]}_{\text{bank wins over competing } f} - p_{HLL} \tag{36}$$

Fintech's indifference condition

$$\pi_f(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right] \overline{F}_b(r)}_{\text{winning both competitors}} \left[\mu_{HHH}(1+r) - 1\right] \tag{37}$$

$$\underbrace{- p_{LHH}\left[1 - m_f + m_f \overline{F}_f(r)\right] - p_{HHL} \overline{F}_b(r)}_{\text{fintech and its one competitor make mistake}} - p_{LHL}. \tag{38}$$

The lowest interest rate pinned down by fintechs' zero profit is given by

$$\underline{r} = \frac{1 - x_f}{\tau}.$$

Accordingly, the bank's profit is given by

$$\pi_b(\underline{r}) = \underbrace{\theta(1+\underline{r})}_{\text{payoff from } h} - \underbrace{\theta - (1-\theta)(1-x_b)}_{\$1 \text{ lent upon } S_b = H} = (1-\theta)(x_b - x_f).$$

Hence, the interest rate range and lender profits are the same as in our baseline model.

As for the lender's pricing, the symmetric condition for two lenders fails

$$1 - m_f + m_f \overline{F}_f(r) \neq \overline{F}_b(r).$$

With three players, there is a new event: one of the competitors makes the same mistake and may burden the l borrower. As the bank and fintechs differ in screening abilities, we no longer have the shifted CDF ($m_w F_w = F_s$). Due to the complexity in lender strategy, later the borrower surplus is characterized by subtracting lender profits from total welfare.

Borrower Surplus From our two-lender analysis, the perverse effect depends on whether high types are hurt. As $\delta \to 0$,

$$\begin{aligned} V_h^{before} =& \text{Total Welfare} - \pi_b \\ =& \theta\overline{r} - (1-\theta)\left\{\underbrace{(1-x_b)}_{b \text{ offers}} + \underbrace{x_b}_{b \text{ rejects}}\left[\underbrace{(1-x_f)\,m_f}_{\text{first } f \text{ offers}} + \underbrace{(1-(1-x_f)\,m_f)}_{\text{first } f \text{ doesn't offer}}(1-x_f)\,m_f\right]\right\} - \pi_b \\ =& \theta\overline{r} - (1-\theta)\left\{(1-x_f) + x_b(1-x_f)\,m_f\,(2-m_f+x_f m_f)\right\} \end{aligned}$$

After mandatory open banking, there are three equilibria, but borrower surplus are equivalent when $\delta \to 0$.[40] For the calculation, we use the asymmetric equilibrium. Let m' denote the probability that fintech makes an offer after mandatory open banking, then

$$V_h^{after} = \text{Total Welfare} = \theta\overline{r} - (1-\theta)\left\{\underbrace{1-x_{f'}}_{\text{first } f \text{ offers}} + \underbrace{x_{f'}}_{\text{first } f \text{ doesn't offer}}\underbrace{(1-x_{f'})\,m'}_{\text{second } f \text{ offers}}\right\}.$$

Under the parameter setting (34), h-type surplus depends on the relative relationship between m' and $m_f\,(2-m_f+xm_f)$.

The bank's profits before open banking and the fintechs' profits after open banking show the

[40] In the symmetric equilibrium, withdrawing with probability $1-m$ loses the NPV from h type

$$\theta\overline{r}\cdot(1-m)^2$$

but avoids loss from l type

$$(1-\theta)\cdot\left[\underbrace{(1-x)(1-m)+x}_{\text{Other fintech not serving}}\right]\underbrace{(1-x)(1-m)}_{\text{withdraw upon} H}.$$

In equilibrium these two effects cancel out exactly

$$(1-m)\cdot\{\theta\overline{r}\,(1-m) - (1-\theta)(1-x)(1-m+xm)\} = 0.$$

following relationships between m_f, m', and x:

$$\pi_b = p_{HHH}(1-m_f)^2[\mu_{HHH}(1+\overline{r})-1] - 2p_{HHL}(1-m_f) - p_{HLL} \to 0$$
$$\Rightarrow (1-m_f)^2\frac{\overline{r}}{\underline{r}} - 1 + (1-x)m_f(2-m_f+m_f x) \to 0; \tag{39}$$

$$\pi_f = p_{HH}(1-m')[\mu_{HH}(1+\overline{r})-1] - p_{HL} = 0$$
$$\Rightarrow (1-m')\frac{\overline{r}}{\underline{r}} - 1 + m'(1-x) = 0. \tag{40}$$

We can rearrange the above two equations ($\underline{r}$ are the same as $x_f \nearrow x_b \nearrow x_{f'} \equiv x$),

$$\underbrace{(1-m_f)^2\left[\frac{\overline{r}}{\underline{r}} - (1-x)\right] - x + m_f^2 x(1-x)}_{LHS \text{ from } (39)} \to \underbrace{(1-m')\left[\frac{\overline{r}}{\underline{r}} - (1-x)\right] - x}_{LHS \text{ from } (40)} = 0,$$

which implies

$$(1-m_f)^2 < (1-m').$$

Plug this back into (39) and (40), we have

$$m' < m_f(2-m_f+xm_f) \Leftrightarrow V_h^{before} < V_h^{after}.$$

Therefore, high types always benefit from mandatory open banking. Our analysis also implies that total welfare is higher in the case of two lenders than with three lenders. This results from our bad-news information structure: l types are more likely to receive an offer with more lenders. One can verify that the total welfare with a monopolist lender is even higher (high types are better off with two lenders as compared with one monopolist due to competition).

C.3 Proof of Proposition ??

For notational convenience, we denote by $\Delta V_i^{\xi,OB} \triangleq V_i^{\xi,OB}(\tau_+) - V_i^{\xi}(\tau_-)$ the i-type's incentive to sign up. The sign-up equilibrium is a collection of tech-savvy borrowers' sign-up decisions $\{\sigma_i\}$, and beliefs about the average credit quality in each market segment $\{\tau_-, \tau_+\}$, such that a) $\{\tau_-, \tau_+\}$ are determined by the Bayes' rule and characterized in (12); b) $\{\sigma_i\}$ satisfy borrowers' incentive compatibility conditions that are similar to (13) with surplus $V_i^{\xi}(\tau_-)$ for not signing up and $V_i^{\xi,OB}(\tau_+)$ for signing up, given lenders' pricing strategies $\left\{m_{j+}^{\xi,OB}, \lambda_{j+}^{\xi,OB}, F_{j+}^{\xi,OB}\right\}$ and $\left\{m_{j-}^{\xi,OB}, \lambda_{j-}^{\xi,OB}, F_{j-}^{\xi,OB}\right\}$ respectively for borrowers who opted in and who opted out.

Contrary to Subsection **??**, now the threshold of ξ, which decides the lender strategy in the opt-out segment, is endogenous and depends on τ_- (for borrowers who signed up, ξ does not affect the structure of lender competition). We first characterize the case with $\xi < \phi(\bar{r};\tau)$ and the case with $\xi > \phi(\bar{r};\rho\tau)$, where lender strategies in the opt-out segment respectively follow Case 1 and Case 3 in Proposition **??**; then we characterize the equilibrium in the case with $\phi(\bar{r};\tau) \leq \xi \leq \phi(\bar{r};\rho\tau)$.

Small ξ Case: $\xi < \phi(\bar{r};\tau)$

Proof. First we show that when $\tau_- \leq \tau$, the low-type have a higher willingness to sign up. The ξ threshold of lender strategy in the opt-out pool is $\phi(\bar{r};\tau_-)$. Note that Condition **??** ensures $\bar{r}\tau_- \geq 1 - x_f$. When $\tau_- \leq \tau$, we have $\phi(\bar{r};\tau_-) \geq \phi(\bar{r};\tau) > \xi$, so for the opting-out borrowers, the lender strategy and borrower surplus follow Case 1 in Proposition **??**. Then for the high-type to be willing to sign up,

$$V_h^{\xi}(\tau_-) = V_h(\tau_-) \overset{\text{willing to sign up}}{\leq} (1-\xi)\, V_h(\tau_+) = V_h^{\xi,OB}(\tau_+).$$

Hence $V_h(\tau_-) < V_h(\tau_+)$ and $\tau_- < \tau_+$. With the better inference and the effects of ξ-event on the low-type shown in (**??**) and (**??**), the low-type must strictly prefer to sign up:

$$V_l^{\xi}(\tau_-) < V_l(\tau_-) < V_l(\tau_+) < V_l^{\xi,OB}(\tau_+).$$

This result rules out equilibrium where a higher proportion of high-type borrowers sign up, $\sigma_h \geq \sigma_l > 0$, under which $\tau_- \leq \tau$ follows and the low-type have higher willingness to sign up. If $1 > \sigma_h > 0$, then the low-type must strictly prefer signing up and $\sigma_l = 1 > \sigma_h$. If $\sigma_h = 1$, then $\sigma_l = 1$, but $\tau_- = \tau_+ = \tau$ contradicts with the high-type's sign up incentive.

We now rule out that a larger proportion of the low-type would sign up in equilibrium, i.e., $\sigma_l > \sigma_h > 0$ and hence $\tau_- > \tau > \tau_+$. In this case, the endogenous ξ threshold $\phi(\bar{r};\tau_-) < \phi(\bar{r};\tau)$ and lender competition in the opt-out pool may not always follow one case in Proposition **??**. If $\xi < \phi(\bar{r};\tau_-)$, the competition follows Case 1 in Proposition **??**, but $\tau_- > \tau > \tau_+$ violates the high-type's sign up incentive. If $\xi = \phi(\bar{r};\tau_-)$ we show later that it must be $\sigma_l < \sigma_h$; and if $\phi(\bar{r};\tau_-) < \xi < \phi(\bar{r};\tau)$, we show later that $\sigma_h = 1, \sigma_l = 0$. The last two cases have $\sigma_l < \sigma_h$ and thus contradict the premise that "a larger proportion of low-type would sign up in equilibrium."

Hence the only possible equilibrium is $\sigma_h = \sigma_l = 0$ and $\tau_- = \tau_+ = \tau$, under which the lender strategy is Case 1 in Proposition **??**. We introduce $\hat{\tau}$ as the threshold τ_+ for the high-type to be indifferent to sign up, so

$$V_h(\tau) = (1-\xi)\, V_h(\hat{\tau}).$$

If the off-equilibrium belief for anyone who signs up satisfies $\tau_+ < \hat{\tau}$, high-type borrowers do not sign up, and the low-type also do not want to sign up to be revealed.

Therefore, in the unique equilibrium nobody signs up and the off-equilibrium belief satisfies $\tau_+ < \hat{\tau}$. □

Large ξ Case: $\xi > \phi(\overline{r}; \rho\tau)$

Proof. Note that $\tau_- = \rho\tau$ is the lower bound of τ_-, and is reached when all tech-savvy high-type sign up, $\sigma_h = 1$, but none of the low-type signs up, $\sigma_l = 0$. Hence, for any possible equilibrium belief τ_-, we have $\xi > \phi(\overline{r}; \rho\tau) \geq \phi(\overline{r}; \tau_-)$: lender competition for borrowers who did not sign up always follows Case 3 in Proposition **??**.

As it is a dominant strategy for the l-type borrower not to sign up, we have $\sigma_l = 0$. Then if anyone were to sign up, they must be a high-type borrower and $\tau_+ = \infty$. As a result, in the non–ξ-event, lenders compete for the opt-in segment à la Bertrand: lenders always charge $r = \underline{r}^{\xi,OB} = \frac{1-x_f}{\tau_+} = 0$. Then the expected interest rate after open banking is $\xi\overline{r}$, and is smaller than that before open banking, $(1-\xi)\,\mathbb{E}\left[\min\left\{r_b^\xi, r_f^\xi\right\}\right] + \xi\mathbb{E}\left[r_f^\xi\right]$:

$$\begin{aligned}\xi\overline{r} - \left[(1-\xi)\,\mathbb{E}\left[\min\left\{r_b^\xi, r_f^\xi\right\}\right] + \xi\mathbb{E}\left[r_f^\xi\right]\right] &= \xi\overline{r} - \left[(2-\xi)\,\xi\overline{r} + (1-\xi)^2\,\frac{(1-x_b)(1-x_f)}{\tau_-}\right] \\ &= -\xi(1-\xi)\,\overline{r} - (1-\xi)^2\,\frac{(1-x_b)(1-x_f)}{\tau_-} < 0.\end{aligned}$$

Therefore in the unique sign-up equilibrium, $\sigma_h = 1$ and $\sigma_l = 0$. □

Intermediate ξ Case: $\phi(\overline{r}; \tau) < \xi < \phi(\overline{r}; \rho\tau)$

Proof. **Step 1.** We argue that in equilibrium $\xi = \phi(\overline{r}; \tau_-)$ always holds so that the lender competition in the opt-out segment switches structures. Otherwise, if in equilibrium $\xi < \phi(\overline{r}; \tau_-)$, nobody would sign up and $\tau_- = \tau$, which contradicts the inequality $\phi(\overline{r}; \tau) \leq \xi$; if $\xi > \phi(\overline{r}; \tau_-)$, only tech-savvy high-type borrowers opt in and $\tau_- = \rho\tau$ which contradicts $\xi \leq \phi_-(\overline{r}; \tau_- = \rho\tau)$. Hence, when $\phi(\overline{r}; \tau) \leq \xi \leq \phi(\overline{r}; \rho\tau)$, in equilibrium ξ is on the cutoff $\xi = \phi(\overline{r}; \tau_-)$.

Step 2. We argue that in equilibrium, $\sigma_l \in (0,1)$ and $\sigma_h > 0$. Suppose not; we prove by contradiction.

1. Say $\sigma_l = 0$. If $\sigma_h = 0$, then $\tau_- = \tau_+ = \tau$ and $\xi > \phi(\overline{r}; \tau_-)$, and lenders compete for the opt-out segment following Case 3 in Proposition **??**, which leads to $\sigma_h = 1$, $\sigma_l = 0$, which is a contradiction. If $\sigma_h > 0$, then $\tau_+ = +\infty$ and, for a borrower who signs up, lenders always make an offer upon H; it follows that low-type borrowers must be at least indifferent to sign up, which is a contradiction.

2. Hence, $\sigma_l > 0$ in equilibrium, which implies that some high-type borrowers must sign up (i.e., $\sigma_h > 0$); otherwise the low-type fully reveal themselves in the opt-in segment and lenders do not participate.

3. We now rule out the case of $\sigma_l = 1$, under which $\tau_- \geq \tau$ and $\xi > \phi(\overline{r}; \tau) \geq \phi(\overline{r}; \tau_-)$. Lender competition in the opt-out segment leads to sign-up strategies $\sigma_h = 1$, $\sigma_l = 0$, which is a contradiction.

Step 3. Now we derive the equilibrium sign-up behaviors. From $\phi(\bar{r};\tau_-)=\xi$, we have

$$\tau_- = \frac{1-x_f}{\bar{r}}\left(\frac{x_b}{\xi}+1-x_b\right). \tag{41}$$

The fintech's offering probability $m_{f-}^{\xi,OB}$ in the opt-out segment and beliefs τ_+, τ_- make low-type borrowers indifferent (i.e., $1>\sigma_l>0$) and make high-types either indifferent or strictly prefer to sign up (i.e., $\sigma_h>0$). Specifically, borrower surplus for not signing up are given by

$$\begin{aligned}
&V_{h,-}^{\xi,OB}(\tau_-)=V_h(\tau_-),\\
&V_{l,-}^{\xi,OB}(\tau_-)=(1-\xi)\underbrace{\left[1-x_b\left(x_f+(1-x_f)\left(1-m_{f-}^{\xi,OB}\right)\right)\right]}_{\text{prob at least one loan}}+\xi\underbrace{(1-x_f)\,m_{f-}^{\xi,OB}}_{\text{prob fintech loan}},
\end{aligned}$$

where $m_{f-}^{\xi,OB}$ versus mass point at $r=\bar{r}$ only influences the probability of receiving a loan but does not affect the expected interest rate. For borrowers who signed up, surplus $V_{i,+}^{\xi,OB}(\tau_+)$ are the same as (**??**) and (**??**) except for adjusted belief τ_+.

For the high-type, there are two subcases to consider.

1. Suppose that the high-type are indifferent to sign up; then τ_+ and $m_{f-}^{\xi,OB}\geq 1-\phi(\bar{r};\tau_-)$ make both types of borrowers indifferent:[41] $V_{i,-}^{\xi,OB}(\tau_-)=V_{i,+}^{\xi,OB}(\tau_+)$, $i=h,l$. Hence, we have[42]

$$\phi_+(\bar{r})=\frac{2x_b+(1+\xi)(1-x_b)-\sqrt{\left[2x_b+(1+\xi)(1-x_b)\right]^2-4\xi\left(x_b+(1-x_b)\xi\right)}}{2\left(x_b+(1-x_b)\xi\right)}, \tag{43}$$

and

$$m_{f-}^{\xi,OB}=1-\frac{(1-\xi)\,x_b\phi_+(\bar{r})}{\xi+(1-\xi)\,x_b}. \tag{44}$$

[41] Equilibrium $m_{f-}^{\xi,OB}$ is well defined and unique. The low-type's indifference condition is equivalent to

$$\Delta V_l^{\xi,OB}=(1-x_f)\left[\left(1-m_{f-}^{\xi,OB}\right)\left(\xi+(1-\xi)\,x_b\right)-(1-\xi)\,x_b\phi_+(\bar{r})\right],$$

where $\phi_+(\bar{r})\equiv\phi(\bar{r};\tau_+)$. The inequality $m_{f-}^{\xi,OB}\geq 1-\phi(\bar{r};\tau_-)$ is satisfied, because when $m_{f-}^{\xi,OB}=1-\phi(\bar{r};\tau_-)$, the low-type strictly prefer to sign up as $\phi_-(\bar{r})\left(\xi+(1-\xi)\,x_b\right)>(1-\xi)\,x_b\underbrace{\phi_+(\bar{r})}_{<\phi_-=\xi}$, and when $m_{f-}^{\xi,OB}=1$, the low-type strictly prefer to opt out. Note that $\Delta V_l^{\xi,OB}$ is monotonic in $m_{f-}^{\xi,OB}$, so $m_{f-}^{\xi,OB}$ is unique.

[42] It follows that $\phi_+(\bar{r})$ satisfies the following quadratic equation,

$$\left(x_b+(1-x_b)\,\xi\right)\phi_+^2-\left[2x_b+(1+\xi)(1-x_b)\right]\phi_++\xi=0. \tag{42}$$

It has two positive roots, and only the smaller root is smaller than 1. Later we study τ_+; since τ_+ and $\phi_+$are negatively related, τ_+ takes the larger root.

From belief-updating rules $\tau_+ = \tau\frac{\sigma_h}{\sigma_l}$ and $\tau_- = \tau\frac{\rho+(1-\rho)(1-\sigma_h)}{\rho+(1-\rho)(1-\sigma_l)}$, we solve for

$$\sigma_h = \frac{\frac{\tau_+}{\tau_-} - \frac{\tau_+}{\tau}}{(1-\rho)\left(\frac{\tau_+}{\tau_-} - 1\right)} \text{ and } \sigma_l = \frac{\frac{\tau}{\tau_-} - 1}{(1-\rho)\left(\frac{\tau_+}{\tau_-} - 1\right)}, \tag{45}$$

where τ_- is determined in (41) and τ_+ is determined by (43) and (6). Note that $\frac{\partial}{\partial\tau_-}\phi(\overline{r};\tau_-) < 0$ implies that $\tau_- < \tau < \tau_+$ for $\xi > \phi(\overline{r};\tau)$ and $\phi(\overline{r};\tau_-) = \xi$. As a result, $\sigma_h > \sigma_l$ from belief-updating rule $\tau_+ = \tau\frac{\sigma_h}{\sigma_l}$. This observation completes the earlier proof of a unique sign-up equilibrium under " **Small** ξ **Case**" (i.e., $\xi < \phi(\overline{r};\tau)$) where we rule out $\tau_+ > \tau > \tau_-$ with $\sigma_l > \sigma_h$.

2. Now suppose that $\sigma_h = 1$. From belief updating, we have

$$\sigma_l = \frac{1 - \frac{\tau}{\tau_-}\rho}{1-\rho}, \text{and } \tau_+ = \frac{\tau(1-\rho)}{1 - \frac{\tau}{\tau_-}\rho},$$

and $m_{f-}^{\xi,OB}$ is determined as in (44).

3. Note that when $\xi \to \phi(\overline{r};\rho\tau)$, we have $\tau_- \to \rho\tau$ and $\tau_+ \to +\infty$, under which

$$V_{h,+}^{\xi,OB}(\tau_+) \to (1-\xi)\,\overline{r} > V_{h,-}^{\xi,OB}(\tau_-) = \underbrace{(1-\phi(\overline{r};\tau_-))}_{=1-\xi}(\overline{r} - \underline{r}_-).$$

Hence, high-type borrowers strictly prefer to sign up (the case in point 2), and $\sigma_h = 1$ (at the same time, $\sigma_l \to 0$). As at the other endpoint $\xi = \phi(\overline{r};\tau)$, we have $\tau_- = \tau$ and thus $\sigma_h = \sigma_l = 0$. By continuity, there exists a $\tilde{\xi} \in (\phi(\overline{r};\tau), \phi(\overline{r};\rho\tau))$ such that when $\xi < \tilde{\xi}$, the high-type are indifferent about signing up (the case in point 1).

□

C.4 Omitted Proof of Proposition ??

Proof. We study the total profits for the financial sector $\Delta\pi_b^{\xi,OB} + \Delta\pi_f^{\xi,OB}$, and give sufficient conditions for them to rise after open banking. Note that $\phi(\overline{r};\tau_-) = \xi$ implies that $\frac{\overline{r}\tau_-}{1-x_f} - 1 = \frac{\xi x_b}{1-\xi}$, so we have

$$\Delta\pi_b^{\xi,OB} + \Delta\pi_f^{\xi,OB} = \frac{(1-\xi)(1-x_f)\,x_b}{1+\tau}\left[1 - \frac{\phi(\overline{r};\tau_-)}{\phi(\overline{r};\tau)} + (1-\rho)\,\sigma_l\right].$$

As $(1-\rho)\sigma_l = \frac{\tau-\tau_-}{\tau_+-\tau_-}$,

$$1-\frac{\phi(\overline{r};\tau_-)}{\phi(\overline{r};\tau)}+(1-\rho)\sigma_l=\underbrace{\frac{(\tau-\tau_-)}{(\tau_+-\tau_-)(\overline{r}\tau_--(1-x_b)(1-x_f))}}_{\text{positive}}(2\overline{r}\tau_--\overline{r}\tau_+-(1-x_b)(1-x_f)). \tag{46}$$

Hence the question boils down to the sign of the last parenthetical term in Eq. (46). Notice that while $\tau_-=\tau$ is continuous at $\xi=\phi(\overline{r};\tau)$, $\tau_+=\tau\frac{\sigma_h}{\sigma_l}$ typically jumps upward at $\xi=\phi(\overline{r};\tau)$ from the left. So it is nontrivial to show that the total financial sector gains even when in the neighborhood of $\xi=\phi(\overline{r};\tau)$.

We use the high-type's indifference curve, which says $1-\frac{1-x_f}{\overline{r}\tau_-}=\left(1-\frac{1-x_f}{\overline{r}\tau_+}\right)\left(\frac{\overline{r}\tau_+-(1-x_f)}{\overline{r}\tau_+-(1-x_f)(1-x_b)}\right)$, which implies that

$$Q(\tau_+)\equiv(\overline{r}\tau_+)^2-[(1+x_b)\overline{r}\tau_-+(1-x_b)(1-x_f)]\overline{r}\tau_++(1-x_f)\overline{r}\tau_-=0.$$

We then try to ensure that $\tau_+<2\tau_--\frac{(1-x_b)(1-x_f)}{\overline{r}}$ (so that the last parenthetical term in Eq. (46) is positive), by checking the sign of $Q\left(\tau_+=2\tau_--\frac{(1-x_b)(1-x_f)}{\overline{r}}\right)$, which equals

$$(2\overline{r}\tau_--(1-x_b)(1-x_f))^2-[(1+x_b)\overline{r}\tau_-+(1-x_b)(1-x_f)](2r\tau_--(1-x_b)(1-x_f))+(1-x_f)\overline{r}\tau_-$$

$$=\overline{r}\tau_-\left[\underbrace{2(1-x_b)\overline{r}\tau_--(5-x_b)(1-x_b)(1-x_f)+(1-x_f)}_{M(\xi)}\right]+\underbrace{2(1-x_b)^2(1-x_f)^2}_{>0}.$$

Because $Q(\cdot)$ is quadratic and opens upward, and we take the larger solution (see footnote 42), to ensure $Q\left(\tau_+=2\tau_--\frac{(1-x_b)(1-x_f)}{\overline{r}}\right)>0$, we need

$$M(\xi)\equiv2(1-x_b)\overline{r}\tau_-(\xi)-(5-x_b)(1-x_b)(1-x_f)+(1-x_f)>0$$

for $\tau_-(\xi)$ when $\xi\in\left[\phi(\overline{r};\tau),\tilde{\xi}\right]$. (Note, $(1-x_b)^2(1-x_f)^2$ will be at higher order when x_j's are close to 1, so this can be ignored). Because τ_- is decreasing in ξ, it is equivalent to ensure that $M(\cdot)>0$ at both ends.

1. When $\xi=\phi(\overline{r};\tau)$, $\tau_-(\xi)=\tau$, so we require that (recalling $\rho\overline{r}\tau\geq1-x_f$ in (**??**))

$$\frac{2}{\rho}(1-x_b)-(5-x_b)(1-x_b)+1>0. \tag{47}$$

2. When $\xi = \tilde{\xi}$, we have $\sigma_h = 1$, which implies that

$$\tau_{-}\left(\tilde{\xi}\right) = \frac{\tau_{+}\left(\tilde{\xi}\right)}{\tau_{+}\left(\tilde{\xi}\right) - (1-\rho)\,\tau}\rho\bar{r}\tau \geq \frac{\tau_{+}\left(\tilde{\xi}\right)}{\tau_{+}\left(\tilde{\xi}\right) - (1-\rho)\,\tau}(1-x_f)\,.$$

Thus $M\left(\tilde{\xi}\right) > 0$ requires that

$$2\,(1-x_b)\,\frac{\tau_{+}\left(\tilde{\xi}\right)}{\tau_{+}\left(\tilde{\xi}\right) - (1-\rho)\,\tau} - (5-x_b)\,(1-x_b) + 1 > 0, \tag{48}$$

which is easy to verify ex post once we have solved for $\tau_{+}\left(\tilde{\xi}\right)$.

In sum, (47) and (48) guarantee that the financial sector gains after open banking when $\xi \in \left[\phi\left(\bar{r};\tau\right), \tilde{\xi}\right]$ (note, these conditions are also necessary if $\rho\bar{r}\tau = 1 - x_f$ and for sufficiently large x_j's). □