

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 either better borrower screening or targeting by fintech lenders. 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.

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

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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

¹The 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.

²See 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.

³See 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

⁴For 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.

⁵This 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.” We study two types of data that borrowers can share under open banking. The first contains information on borrowers’ credit quality, which affects the lending *cost* of financial institutions. The other type of data potentially reveals borrowers’ *preferences* for the fintech loan, and these data might enable

the fintech to offer targeted loans to exploit borrowers.

Section 3 examines credit-quality data sharing. 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 “overempowers” 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

⁶For 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.

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

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.

Section 4 studies the effects of data sharing on customer preferences. We shut down the previous channel of data sharing on credit quality in Section 3, and this parallel examination has two goals. First, as explained in Section 4.1, one key advantage of fintechs is offering targeted loans once equipped with better customer preference information. Second, 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 when sharing data about preferences.

We assume that borrowers are subject to some random shocks under which they can only take the fintech’s loan; for instance, some borrowers happen to need a quick loan and only the fintech can process it with “immediacy.”⁸ With the aid of big data technology that can integrate, say, borrowers’ social data and digital footprints together with their bank account information, open banking allows the fintech to identify these events. Accordingly, the fintech can “target” some borrowers by performing precision marketing, or in words, “delivering the right offer at the right time to the right customer.” The borrowers, once hit by preference shocks, resemble the “captured” consumers in Varian (1980) who consider only one seller’s offer.

We fully characterize the equilibrium outcome as a function of the probability of preference events. We link this probability to the development stage of the fintech lender’s business model, as this probability directly measures the number of consumers potentially “captured” by the fintech. We then show a similar welfare result as 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.

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 customer preference. Though the ensuing disruption to the

⁸Transaction records from the borrower’s bank allow fintech lenders to infer the borrower’s more detailed demographic and credit information, by analyzing, say, the income and occupation revealed from direct deposits, consumption habit, and other information. This inference, combined with browsing and location data and their much shorter loan application processing time, allows fintech lenders to assess and meet the borrower’s demand of “immediacy.” This could be useful, for instance, for borrowers traveling abroad who need loans in foreign currencies on the spot, or consumers on e-commerce platforms with impulse purchase needs.

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.⁹ 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 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).¹⁰ 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

⁹Lending 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).

¹⁰In 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.

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 \(2006\)](#).¹¹ 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](#), 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](#)).¹² [Berg, Burg, Gombović, and Puri \(2020\)](#) find that even simple 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.

On the theoretical front, [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

¹¹These 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.

¹²Blockchain 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 Brunnermeier \(Working Papers\)](#).

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.¹³

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.¹⁴ 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 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

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

¹³In 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 unravelling mechanism in Milgrom (1981) implies that everyone shares the data in equilibrium.

¹⁴Recent 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.

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),¹⁵ 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} .¹⁶

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 3.4.

Following Broecker (1990), we assume that each lender receives an independent and

¹⁵Usury 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.

¹⁶In 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.

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:

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

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).¹⁷

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.¹⁸ (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 simplicity, we assume that the two lenders have the same funding costs which we normalize to 1.¹⁹

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 \bar{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

¹⁷For different information structures, see [Chu and Wei \(2021\)](#), [Hau, Huang, Shan, and Sheng \(2019\)](#) and others.

¹⁸Although 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.

¹⁹We 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.

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 $r = \bar{r}$ if this expected repayment rate times $1 + \bar{r}$ exceeds the cost 1. This requires

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

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 nonmonetary 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,²⁰ though this assumption plays little role as our welfare analysis focuses on the Pareto criterion for consumers without transfer.

2.3 Equilibrium Characterization

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

2.3.1 Preliminary analysis

Let

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

²⁰Specifically $0 < \delta < 1$, 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.

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.²¹

We introduce some notation to characterize the mixed-strategy equilibrium that arises. 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 \bar{r} . For our subsequent analysis, it is more convenient to use the survival function $\bar{F}_j(r) \equiv 1 - F_j(r)$.

²¹In 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

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

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 π_j be the lender j 's equilibrium (expected) profit.

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

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

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 $m_w \bar{F}_w(r)$); 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

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

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

$$p_{HH} \bar{F}_s(r) [\mu_{HH} (1 + r) - 1] - p_{LH} = 0. \quad (5)$$

To make this equation hold for r close to \bar{r} , we need F_s to have a mass point at the top. Let $\lambda_s \equiv \lim_{r \uparrow \bar{r}} \bar{F}_j(r) \in [0, 1)$ 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 $(r, \pi_s, m_w, \lambda_s)$ and the two distributions. For notational convenience, we define

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

which is $\bar{F}_s(r)$ solving (5). Note that $\phi(r)$ depends on primitive parameters x_w , x_s , and τ , and Assumption (1) implies that $\phi(\bar{r}) \in (0, 1)$. 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:²²

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 $\bar{F}_s(r) = \phi(r)$, which has support $[\underline{r}, \bar{r}]$ with $\underline{r} = \frac{1-x_w}{\tau}$ and has a mass point of size $\lambda_s = \phi(\bar{r})$ at \bar{r} ; and*
3. *the weak lender makes an offer with probability $m_w = 1 - \phi(\bar{r})$ upon seeing a high signal, and when it makes an offer, the interest rate is randomly drawn from the distribution*

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

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

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 $r \in [\underline{r}, \bar{r})$, the two distributions satisfy

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

Since $m_w = 1 - \phi(\bar{r}) < 1$, 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

²²It 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., $m_s = m_w < 1$). In these two classes 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 asymmetric equilibria.

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

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

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 $\mathbb{E}[r_s] = \underline{r} + \int_{\underline{r}}^{\bar{r}} \bar{F}_s(r) dr$ and $\mathbb{E}[\min(r_w, r_s)] = \underline{r} + \int_{\underline{r}}^{\bar{r}} \bar{F}_s(r) \bar{F}_w(r) dr$. Then a high-type borrower's expected surplus is

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

which is the high-type's pecuniary payoff from the project and equals \bar{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.)²³

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 $m_w = 1 - \phi(\bar{r})$, a low-type borrower's expected surplus is

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

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 $\frac{\bar{r}}{\underline{r}} < 1 + \sqrt{x_s}$.*

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 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;²⁴ but at the same time, the screening ability gap Δ widens and the weak lender suffers due to a more severe winner's

²³Here we use the interpretation that a borrower is a small business firm whose project yields a net return \bar{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 \bar{r} , in which case the expected surplus is $V_h(x_w, x_s, \tau) = u - \underline{r} - (\bar{r} - \underline{r}) \phi(\bar{r}) = u - \bar{r} + (\bar{r} - \underline{r})(1 - \phi(\bar{r}))$. Since $u - \bar{r}$ is a constant, our analysis below carries over to this interpretation as well.

²⁴The improved screening efficiency has no effect on the high types, as the strong lender absorbs all the rent by enjoying increased profits.

course, 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 Open Banking: Credit Information Sharing

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.

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,²⁵ 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

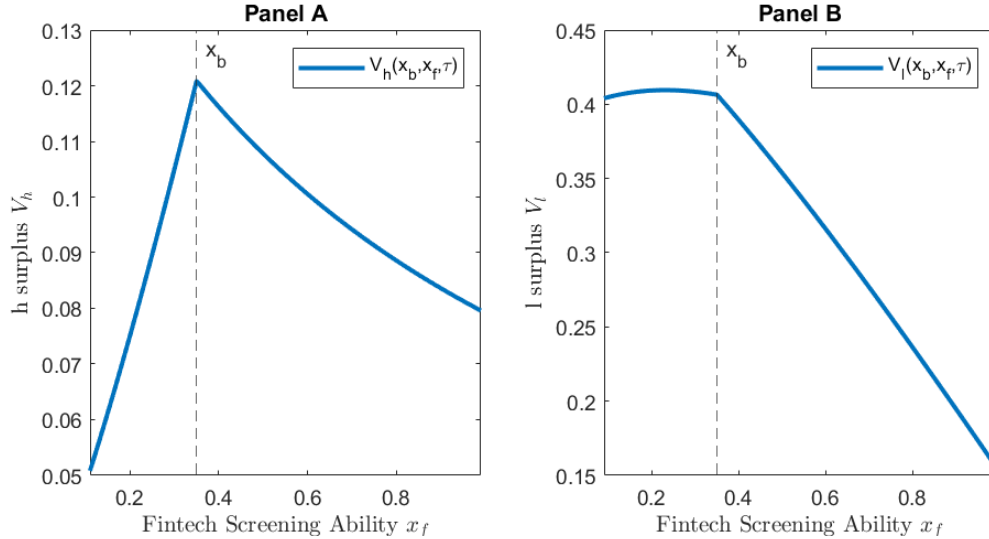
Suppose first that all borrowers are required to sign up for open banking. This improves the fintech’s screening ability, but it does not cause market segmentation since all borrowers have to share their data, so the lenders’ prior beliefs of the average credit quality remain unchanged. This is not the 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

²⁵Item [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 $\bar{r} = 0.36$, $x_b = 0.35$, $\delta = 0.5$, and $\tau = 3.4$.

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 $V_i(x_b, x'_f, \tau) > V_i(x_f, x_b, \tau)$. (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 $V_l(x_f = 0, x_b, \tau) < V_l(x_f = x_b, x_b, \tau)$ 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 noneconomic 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.²⁶ Then the two lenders compete in two separate market segments: 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,

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

Intuitively, when high-type tech-savvy borrowers are more likely to sign up for open banking,

²⁶The 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.

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:

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

If a borrower chooses to sign up, she will be classified in the market segment characterized by (x_b, x'_f, τ_+) 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

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

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) $\{m_j^+, F_j^+\}$ and $\{m_j^-, F_j^-\}$ 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.²⁷

²⁷This 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.

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. $V_l(x_f, x_b, \tau) \leq V_l(x_b, x'_f, \tau)$. 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. $V_l(x_f, x_b, \tau) > V_l(x_b, x'_f, \tau)$ and $V_l(x_f, x_b, \rho\tau) < V_l(x_b, x'_f, \infty)$. 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. $V_l(x_f, x_b, \rho\tau) \geq V_l(x_b, x'_f, \infty)$. 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 $\sigma_h = 1$).

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.²⁸ 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 $\bar{\tau}$.

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 $V_l(x_f, x_b, \tau) > V_l(x_b, x'_f, \tau)$ 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 $V_l(x_f, x_b, \rho\tau) < V_l(x_b, x'_f, \infty)$ 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.²⁹ 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.

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-*

²⁸Recall 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_+ .

²⁹One needs to specify a proper off-equilibrium belief to sustain the equilibrium if the condition $V_l(x_f, x_b, \tau) \leq V_l(x_b, x'_f, \tau)$ does not hold.

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:

$$V_h(x_f, x_b, \tau_-) \leq V_h(x_b, x'_f, \tau_+) < V_h(x_f, x_b, \tau), \quad (14)$$

and

$$V_l(x_f, x_b, \tau_-) = V_l(x_b, x'_f, \tau_+), \quad (15)$$

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 $V_h(x_b, x'_f, \tau) <$

$V_h(x_f, x_b, \tau)$ and $V_l(x_b, x'_f, \tau) < V_l(x_f, x_b, \tau)$, 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 observation is that non-tech-savvy borrowers always (weakly) suffer due to open banking with voluntary sign-up, again 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 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.

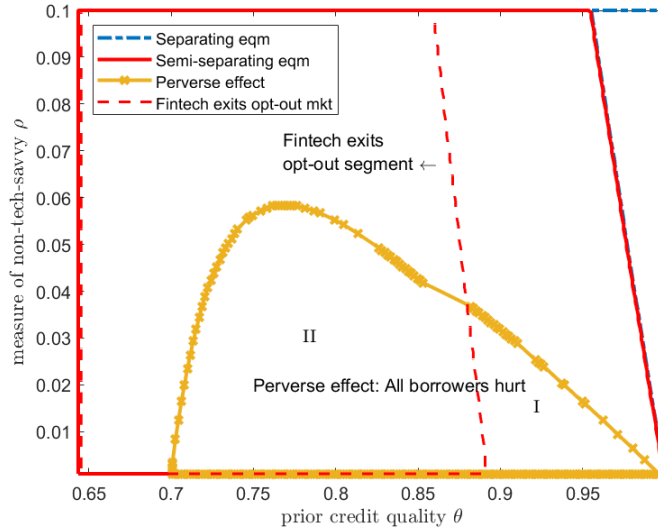
Finally, we comment on how open banking affects profit and overall welfare. When both market segments have two active lenders, both lenders make a positive profit (the bank earns from the opt-out market segment and the fintech earns from the opt-in market segment), but the bank earns less than before. 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.

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-

Figure 2: Voluntary Sign-Up Equilibrium



The range of various non-trivial voluntary sign-up equilibria in the parameter space of $(\theta = \frac{\tau}{1+\tau}, \rho)$. 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: $\bar{r} = 0.36$, $x_b = 0.4$, $x_f = 0.35$, and $x_{f'} = 0.8$. (In this configuration of parameters there is no pooling equilibrium; condition (1) holds always.)

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 noneconomic privacy concerns are less severe.)

3.4 Multiple Fintech Lenders

We have adopted the simplest model structure—two lenders—to study credit market competition. Although it is consistent with search friction in practice,³⁰ open banking could substantially enlarge the consideration set of borrowers (Clark, Houde, and Kastl, 2020) by alleviating search frictions and/or expanding 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 have different lending costs (winner’s curse) but offer identical products, it is impossible for all three to survive (for

³⁰For 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.

a formal proof, see Online Appendix C). Then under mandatory open banking, if the two fintechs’ screening abilities are far apart from each other after obtaining borrowers’ banking data, the perverse effect still arises.

With voluntary sign-ups, the existence of multiple fintechs also brings more options to borrowers, who can then strategically choose favorable fintechs with whom to share data. However, equilibrium beliefs may discourage high types from choosing certain fintechs to share data with, and force low types to “follow” high types, which in turn renders the extra options of 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 drastically drop to zero, so the borrower surplus must go up.

We emphasize that a large gap in screening abilities is necessary for the perverse effect only when the shared data is about credit quality information, as we show in the next section.

4 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. We show 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.

4.1 Borrower “Preferences” for Fintech Loans

Taking the baseline model in Section 2, suppose now that each borrower is subject to a preference shock, so that with a probability $\xi > 0$ the borrower can take out loans only from the fintech lender. This event, simply called the ξ -event, is independent of the borrower’s credit quality type. Before open banking, the fintech cannot observe this preference event. However, with open banking, the fintech lender will perfectly observe this event for borrowers signed up for open banking, so the fintech lender will be able to know exactly when borrowers are “locked in” to fintech loans.³¹

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. In the first category, some borrowers strongly prefer fintech loans. For instance, when a consumer shops on an e-commerce platform, she might have a strong preference for “immediacy” (i.e., buying a certain product immediately). If she needs to borrow but has no credit cards, in this case fintech lenders often dominate traditional banks by processing loan applications much faster.³³ With open banking, the transaction records from the borrower’s bank (which may contain important information, say, on the borrower’s consumption habits), together with the borrower’s digital footprint, often enable the fintech lender to better identify the event of demand immediacy.

In the second category, borrowers face a restricted set of available lenders in some circumstances. For example, a borrower could be ineligible for bank loans sometime (e.g., because she happens to be close to the bank’s borrowing limit), or she travels abroad and needs an emergency loan in foreign currency (say for health insurance) unavailable from her bank.

³¹It 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.

³²Precision 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.

³³See, for instance, Fuster, Plosser, Schnabl, and Vickery (2019) for evidence that fintechs are faster at processing loans in the context of housing mortgages.

Open banking provides such information to fintech lenders so that they can then target the borrower more precisely.

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.³⁴

Given that the borrowers in the ξ -event can borrow from the fintech only, they are similar to the “captured” consumers in Varian (1980), though our model offers some new economics thanks to the winner’s curse embedded in the credit market competition (see below). Because ξ directly measures the captured borrowers who can be potentially identified and targeted by fintech lenders, another useful way to think about the magnitude of ξ is that it serves as a proxy for the development of fintech businesses. The case of small ξ corresponds to an underdeveloped “challenger” fintech lender whose business model is in its relative early stage, lacking a clearly defined target market. Over time, once fintech lenders have established their niche markets with more and more captured customers—e.g., young Ivy League graduates who live in major metropolitan cities—they eventually launch certain differentiated products and become profitable with a larger ξ . Shortly, this business development interpretation of ξ will be handy in interpreting some of our comparative static results.

4.2 Competition Equilibrium before Open Banking

4.2.1 The magnitude of ξ

The equilibrium structure of the credit market competition with ξ -event crucially depends on the magnitude of ξ . When

$$\xi \leq \phi(\bar{r}) \triangleq \frac{x_b}{\frac{\tau}{1-x_f}\bar{r} - (1-x_b)} < 1, \quad (16)$$

³⁴Even 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.

the fintech with a weaker screening ability still makes a zero profit, and the equilibrium structure is similar to that in Proposition 1 (i.e., the baseline case of $\xi = 0$). When $\xi > \phi(\bar{r})$, however, both lenders earn a positive profit with a different equilibrium structure. In fact, by simply charging the maximum interest rate \bar{r} (upon seeing a good signal), the fintech gains from borrowers who pass both screenings and are in their ξ -events, but loses from serving borrowers who are rejected by the bank:

$$\underbrace{\xi \cdot p_{HH} [\mu_{HH} (\bar{r} + 1) - 1]}_{\text{profit from } \xi\text{-events with two good signals}} - \underbrace{p_{LH}}_{\text{winner's curse}} = p_{LH} \left(\frac{\xi}{\phi(\bar{r})} - 1 \right). \quad (17)$$

When ξ exceeds the critical value in (16), the gain dominates and hence the fintech with a sufficient measure of captured borrowers earns a positive profit.

4.2.2 Equilibrium characterization before open banking

We use the superscript “ ξ ” to indicate the model with a possible ξ -event. When (16) holds, the bank makes an offer upon seeing a good signal, while the fintech does so with probability $m_f^\xi < 1$, and we have two lenders’ indifference conditions:

$$\begin{aligned} p_{HH} \left(\underbrace{(1 - \xi) \bar{F}_b^\xi(r)}_{\text{win if beats bank}} + \underbrace{\xi}_{\text{win for sure}} \right) [\mu_{HH} (r + 1) - 1] - p_{LH} &= \underbrace{\pi_f^\xi = 0}_{\text{fintech: zero profit}}, \quad (18) \\ \underbrace{(1 - \xi)}_{\text{shrunk market size}} \left\{ p_{HH} \left(1 - m_f^\xi + m_f^\xi \bar{F}_f^\xi(r) \right) [\mu_{HH} (r + 1) - 1] - p_{HL} \right\} &= \underbrace{\pi_b^\xi > 0}_{\text{bank: positive profit}}. \quad (19) \end{aligned}$$

When (16) does not hold, both lenders will make an offer for sure upon seeing a good signal, and so we will have $m_f^\xi = 1$ and $\pi_f^\xi > 0$ in the above two indifference conditions.

Recall $V_i(\tau)$ in (9) and (10); we omit the screening ability variables since they are kept constant in this section. The following proposition reports the details of the equilibrium.

Proposition 5. *Before open banking, the equilibrium with ξ -event are as follows.*

1. When $\xi < \phi(\bar{r})$, the fintech makes a zero profit $\pi_f^\xi = 0$ while the bank makes a profit $\pi_b^\xi = (1 - \xi) \frac{x_b - x_f}{1 + \tau} > 0$. The fintech adopts the same pricing strategy as in Proposition 1 with $m_f^\xi = 1 - \phi(\bar{r})$, and the bank’s pricing strategy is characterized by $\bar{F}_b^\xi(r) = \frac{\phi(r) - \xi}{1 - \xi}$

with $m_b^\xi = 1$. The borrower surpluses are:

$$V_h^\xi(\tau) = V_h(\tau), \quad (20)$$

$$V_l^\xi(\tau) = V_l(\tau) - \xi\delta(1 - x_b)(x_f + (1 - x_f)\phi(\bar{r})). \quad (21)$$

2. When $\xi = \phi(\bar{r})$, there exists a continuum of equilibria indexed by $m_f^\xi \in [1 - \phi(\bar{r}), 1]$, which is the fintech's loan offer probability to a borrower with a good signal. Everything else is identical to case (1), except for the low-type surplus which is given in Appendix A.10.

3. When $\xi > \phi(\bar{r})$, both lenders make positive profits. Upon seeing a good signal both lenders always make an offer (i.e., $m_f^\xi = m_b^\xi = 1$), with interest rate distributions $\bar{F}_b^\xi(r) = \frac{\xi}{1-\xi} \cdot \frac{\phi(r) - \phi(\bar{r})}{\phi(\bar{r})}$ and $\bar{F}_f^\xi(r) = \frac{\xi}{\phi(\bar{r})} \cdot \phi(r)$. The borrower surpluses are

$$V_h^\xi(\tau) = (1 - \xi)^2 \left[\bar{r} - \frac{(1 - x_b)(1 - x_f)}{\tau} \right] < V_h(\tau), \quad (22)$$

$$V_l^\xi = \delta[(1 - \xi)(1 - x_b x_f) + \xi(1 - x_f)]. \quad (23)$$

The third case of a relatively large $\xi > \phi(\bar{r})$ is similar to the Varian-type model (with asymmetric sizes of captured consumers across firms). Thanks to its relatively large base of (potentially) captured borrowers, the fintech—despite its weaker screening ability—always extends loan offers upon seeing a good signal and makes a positive profit. The larger the ξ , the more the captured borrowers, and the higher interest rates from both lenders in the sense of FOSD.

The first case of a relatively small $\xi < \phi(\bar{r})$ is more surprising: the fintech with relatively few captured borrowers takes a pricing strategy that is independent of ξ —more precisely, it is the same as in the baseline $\xi = 0$. The bank, in contrast, prices more aggressively. Why? As is typical in a setting with a mixed-strategy equilibrium, the bank's pricing strategy is determined by the fintech's zero-profit condition (18). But the zero-profit fintech must lose from noncaptured borrowers in equilibrium; for this, the bank bids more aggressively (and earns less), so much so that high-type borrowers lose nothing from the presence of potential ξ -event in Eq. (20). (This result differs from the case of large ξ just discussed above, or more generally, the Varian-type model in which a firm with captured borrowers always earn

a positive profit.³⁵) On the other hand, because the potential ξ -event prevents borrowers from taking bank loans, this hurts low-type borrowers who only care about the chance of receiving a loan.³⁶

Recall that ξ , which measures the number of captured customers, also captures the development stage of the fintech lender’s business model. It is intuitive that an underdeveloped “challenger” fintech lender that lacks a clearly defined targeted market ($\xi < \phi(\bar{r})$) would struggle with their bottom line while those relatively mature fintech lenders that have established their own niche markets would thrive.

Finally, in the knife-edge case (2), when $\xi = \phi(\bar{r})$, there exists a continuum of equilibria indexed by $m_f^\xi \in [1 - \phi(\bar{r}), 1]$, which is the fintech’s probability of making an offer upon seeing a good signal. This explains why low-type borrowers who care only about loan probabilities are affected by the fintech’s policy. In this continuum of equilibria, $m_f^\xi = 1 - \phi(\bar{r})$ corresponds to case (1) with $\xi < \phi(\bar{r})$, while $m_f^\xi = 1$ corresponds to case (3) with $\xi > \phi(\bar{r})$. This continuum of equilibria plays a role when we analyze the model with voluntary sign-up.

4.3 Equilibrium Open Banking with Targeted Loans

We first solve the mandatory sign-up case to highlight the type-dependent incentives to opt in, and then characterize the equilibrium when sign-up is voluntary. To highlight the new role of open banking in this section, we assume that the fintech lender’s screening ability on credit type remains unchanged (i.e., $x'_f = x_f$) after open banking.³⁷ The fintech gains from open banking by taking advantage of the borrowers’ data to extend targeted loans.

4.3.1 Mandatory sign-up

When borrowers are mandated to opt in, the fintech charges borrowers the monopolistic rate \bar{r} in their ξ -events whenever it sees a good signal. For borrowers in their non- ξ -events,

³⁵Also, with open banking our model is a variant of [Varian \(1980\)](#) where only one firm can identify its captured consumers and hence price discriminate accordingly. This scenario, which is quite natural in our context of credit market competition, is rarely considered in the literature on industrial organization.

³⁶The potential ξ -event hurts the low-type borrower, relative to the baseline model, only in the following scenario. The borrower receives a good signal from the bank (which occurs with probability $1 - x_b$) but the fintech does not make any loan (which occurs with probability $x_f + (1 - x_f)\phi(\bar{r})$, as the fintech either receives a bad signal, or a good signal but does not lend). This explains $\xi(1 - x_b)(x_f + (1 - x_f)\phi(\bar{r}))$ in Eq. (21).

³⁷For this reason, we have ignored the screening ability variables in the borrower surplus function in this section.

lenders compete as in Proposition 1, leading a zero profit for the fintech.³⁸ The fintech's expected profit hence is:

$$\pi_f^{\xi, OB} = \xi \cdot \left(\underbrace{\theta \bar{r}}_{\text{profit from high-type}} - \underbrace{(1 - \theta)(1 - x_f)}_{\text{loss from low-type given } H \text{ signal}} \right) = \xi \cdot \frac{\tau \bar{r} - (1 - x_f)}{1 + \tau} > 0. \quad (24)$$

Superscript “ ξ, OB ” indicates the ξ -event model under open banking. For borrower surplus, in the ξ -event, a high-type borrower is charged \bar{r} (hence no rent left), while a low-type borrower receives a loan given a good signal from the fintech (which occurs with probability $1 - x_f$). Therefore the type-dependent borrower surpluses are:

$$V_h^{\xi, OB}(\tau) = (1 - \xi) V_h(\tau), \quad (25)$$

$$V_l^{\xi, OB}(\tau) = (1 - \xi) V_l(\tau) + \delta \xi (1 - x_f), \quad (26)$$

where $V_i(\tau)$ are in (9) and (10). By comparing them to Proposition 5, we have the next proposition on the impacts of open banking (with mandatory sign-up):

Proposition 6. *Compared to the regime before open banking,*

1. *there exists $\hat{\xi} \in (\phi(\bar{r}), 1)$ such that high-type borrowers suffer due to open banking with mandatory sign-up if and only if $\xi \leq \hat{\xi}$, while low-type borrowers suffer if and only if $\xi > \phi(\bar{r})$. Therefore both types of borrower strictly suffer when $\xi \in (\phi(\bar{r}), \hat{\xi})$; and*
2. *open banking with mandatory sign-up helps the fintech but (weakly) harms the bank.*

The fintech benefits from open banking, as it now can price discriminate and offer targeted loans to exploit the borrowers in their ξ -events. The bank strictly suffers when $\xi > \phi(\bar{r})$: after open banking, the fintech with a relatively mature business model will compete more aggressively for non- ξ -event borrowers. When $\xi \leq \phi(\bar{r})$, the fintech adopts the same pricing strategy before and after open banking, and that is why open banking has no impact on the bank.

Open banking has an intriguing type-dependent impact on borrower surplus, which helps us understand the voluntary sign-up equilibrium in the next section. When $\xi < \phi(\bar{r})$ so that the underdeveloped fintech still earns zero profit before open banking, the high type suffer due to open banking, which facilitates the fintech to target their ξ -events. In comparison,

³⁸Without loss of generality, we analyze the model as if ξ -event is unobservable to the bank; see footnote 31.

the low-type gain since they now receive an offer for sure in the ξ -event if the signal is good (but before open banking in the same event, the fintech might not make offers as $m_f^\xi < 1$).

For fintechs with a relatively mature business model so that $\xi > \phi(\bar{r})$, the result concerning the low-type surplus is reversed. Thanks to a sufficiently large number of captured borrowers, before open banking the fintech lender makes a strictly positive profit and always offers a loan upon seeing a good signal. However, after open banking, the fintech can identify captured borrowers perfectly, and as a result it scales back in non- ξ -events ($m_f^{\xi,OB} < 1$ so it randomly drops out without making offers). Low-type borrowers thus prefer opting out of open banking.

For high-type borrowers, they could gain strictly from open banking when $\xi > \hat{\xi}$ for a threshold $\hat{\xi}$; this is again in contrast to being harmed by open banking when ξ is small. To see this result, consider the limiting case of $\xi \rightarrow 1$. Before open banking, knowing that the fintech will be the de facto monopolist, both lenders charge interest rates that converge to \bar{r} . After open banking, the bank—knowing that the fintech can identify captured borrowers perfectly—offers an interest rate independent of ξ . Essentially, price discrimination after open banking leads to monopoly pricing in the ξ -event market segment but a fiercer competition in the non- ξ -event segment; we show that the latter effect dominates when ξ is sufficiently large, and the high-type benefit from open banking.

Proposition 6 delivers a result that is parallel to Proposition 3 in Section 3 on credit quality data sharing: It is possible that both types of borrower strictly suffer due to open banking with mandatory sign-up. Just like in Section 3, this perverse welfare effect can hold even when borrowers voluntarily choose to share their preference data, as we show now.

4.3.2 Voluntary sign-up

Now we study the case with voluntary sign-up. As in Section 3, let ρ be the measure of non-tech-savvy borrowers with an infinite sign-up cost, which is independent of both credit quality type as well as of the preference event.

Recall that the fraction of the tech-savvy type- i borrowers who sign up for open banking is denoted by $\sigma_i \in [0, 1]$, and the updated priors of credit quality in the two opt-in and opt-out market segments are τ_+ and τ_- , respectively, as defined in (12). In this section we further assume that ρ is sufficiently large:

$$\rho\tau\bar{r} > 1 - x_f. \tag{27}$$

The condition says even if $\sigma_h = 1$ (all high-type tech-savvy borrowers opt in) while $\sigma_l = 0$ (all low-type tech-savvy borrowers opt out), lenders still serve both segments thanks to a sufficiently favorable updated opt-out prior τ_- , in light of condition (1).

Crucially, lender competition in the opt-out segment resembles that in Proposition 5 before open banking, but the threshold value for ξ —which is $\phi(\bar{r}; \tau_-)$ —is now endogenous and depends on the updated opt-out prior τ_- . For this reason, we write the dependence of τ_- of $\phi(\bar{r}; \tau_-)$ explicitly; $\phi(\bar{r}; \tau_-)$ is decreasing in τ_- . The following proposition fully characterizes the unique equilibrium that arises, when we vary ξ .

Proposition 7. *When sign-up for open banking is voluntary, the equilibrium with ξ -event can be characterized as follows:*

1. when $\xi < \phi(\bar{r}; \tau)$, there exists a unique equilibrium where no borrowers sign up, i.e., $\sigma_h = \sigma_l = 0$;
2. when $\phi(\bar{r}; \tau) < \xi < \phi(\bar{r}; \rho\tau)$, there exists a unique equilibrium where $\sigma_h > \sigma_l > 0$, so that $\tau_- = \tau \frac{1-(1-\rho)\sigma_h}{1-(1-\rho)\sigma_l}$ satisfies $\xi = \phi(\bar{r}; \tau_-)$; and
3. when $\xi > \phi(\bar{r}; \rho\tau)$, there exists a unique equilibrium where only high-type borrowers sign up, i.e., $\sigma_h = 1$ while $\sigma_l = 0$.

The case of small $\xi < \phi(\bar{r}; \tau)$. When ξ is sufficiently small so the fintech business model is relatively underdeveloped, the unique equilibrium is that nobody signs up for open banking. This explains why the average credit quality in the opt-out segment is $\tau_- = \tau$ (i.e., the prior), and the lender competition in the opt-out segment falls into case (1) of Proposition 5.

There is a “stigma” effect—akin to the one in the context of Fed’s discount window (e.g., [Armantier, Ghysels, Sarkar, and Shrader, 2015](#))—of associating signing up with low credit quality. To see this, as we have pointed out in Proposition 6, fixing the average credit quality, the low-type are more willing to opt in than the high-type. The high-type suffer due to open banking due to fintech exploitation of their ξ -event, while the interest rate-insensitive low-type on the contrary benefits from a greater chance of receiving a loan. It is in sharp contrast to Lemma 2 which concerns sharing credit quality data in Section 3. There, the high-type naturally prefer a more precise screening technology (relative to the low-type); while here, signing up for open banking means exposing the high-type to exploitation by the fintech charging a monopolistic rate (something that the low-type do not care).

The case of large $\xi > \phi(\bar{r}; \rho\tau)$. When ξ is sufficiently large so that the fintech business model is more established, the unique equilibrium is that only high-type (tech-savvy) borrowers opt in. The updated opt-out prior $\tau_- = \rho\tau$, and the equilibrium in the opt-out segment falls into case (3) of Proposition 5.

Again the endogenous credit quality inference is crucial, because the equilibrium is driven by low-type borrowers always preferring to opt out. Eq. (23) in Proposition 5 shows that their opt-out surplus V_l^ξ is independent of τ_- ; in fact, V_l^ξ achieves its upper bound because both the fintech (with a sufficiently large measure of captured borrowers) and the bank always make an offer upon good signals. (Recall that we have assumed a sufficiently large ρ in condition (27) so that the opt-out segment is still profitable enough.) Opting into open banking exposes the low-type to the risk of the fintech (as the weaker lender) not to make loans in their non- ξ -events. No low-type tech-savvy borrower will opt in, leading to the equilibrium inference of opt-in borrowers being a high-type borrower. We show that this favorable credit quality inference is sufficient to convince the high-type to always sign up for open banking in equilibrium, despite the exposure of their ξ -events.

The case of intermediate $\xi \in (\phi(\bar{r}; \tau), \phi(\bar{r}; \rho\tau))$. When ξ falls in the intermediate range, the unique equilibrium takes the form of the knife-edge case (2) in Proposition 5. There, the equilibrium sign-up populations of both (tech-savvy) types endogenously ensure that $\xi = \phi(\bar{r}; \tau_-)$, and we pin down the fintech's loan offering probability m_f^ξ from the two indifference conditions of borrowers.

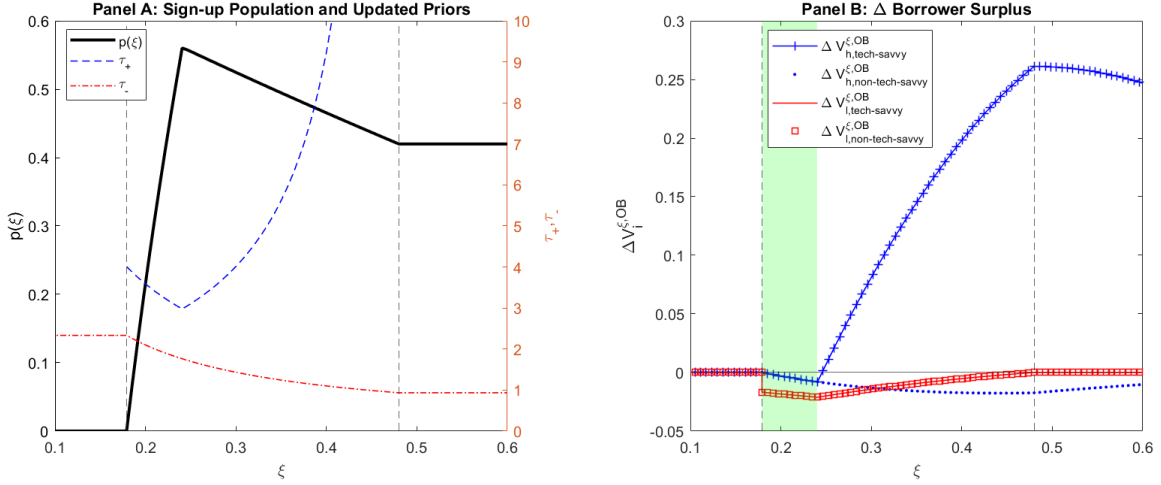
4.4 Impact of Open Banking and Voluntary Sign-Up

Our discussion is based on the following proposition. We first define the sign-up population to be

$$p(\xi) \equiv (1 - \rho)[\theta\sigma_h(\xi) + (1 - \theta)\sigma_l(\xi)]. \quad (28)$$

Proposition 8. *The open banking sign-up population $p(\xi)$ is single peaked at $\tilde{\xi} \in (\phi(\bar{r}; \tau), \phi(\bar{r}; \rho\tau))$. For all $\xi \in [\phi(\bar{r}; \tau), \tilde{\xi}]$, relative to the case before open banking, all borrowers are strictly worse off; the fintech gains while the bank loses; and the financial industry gains under conditions given in the proof.*

Figure 3: Equilibrium Open Banking Sign-Up Population and Borrower Surplus



Panel A plots the sign-up population $p(\xi)$ as a function of ξ (left scale); the updated opt-in and opt-out priors τ_+ and τ_- (right scale). The updated prior τ_+ diverges to ∞ as $\xi \rightarrow \phi(\bar{r}; \rho\tau)$; therefore we cap it at 10. Panel B plots $\Delta V_i^{\xi, OB} \equiv V_i^{\xi, OB} - V_i^\xi$ which captures the impact of open banking on borrower surplus as a function of ξ ; the solid blue lines with crosses (dots) are surplus for the (non-) tech-savvy high-type borrowers, while solid red lines (squares) are surplus for the (non-) tech-savvy low-type borrowers. In the figure, $\phi(\bar{r}; \tau) = 0.18$ and $\tilde{\xi} = 0.24$. Parameter values are $\bar{r} = 1$, $x_b = 0.8$, $x_f = 0.5$, $\delta = 0.5$, $\rho = 0.4$, and $\theta = 0.7$.

4.4.1 Sign-up population and ξ

Panel A in Figure 3 illustrates the total sign-up population and the updated priors in equilibrium, as a function of preference shock ξ . When ξ increases, initially nobody signs up, $p(\xi) = 0$, with the updated opt-out prior τ_- staying at the prior τ . Both types of tech-savvy borrowers start to sign up once ξ exceeds $\phi(\bar{r}; \tau)$, which takes a value of 0.18 in our numerical example. The updated opt-out prior τ_- goes down afterwards, while the updated opt-in prior τ_+ in the opt-in segment always sits above the prior τ . The total sign-up population as shown peaks at $\tilde{\xi} = 0.24$ then goes down afterward; this is because $\sigma_h = 1$ while σ_l decreases for $\xi > \tilde{\xi}$, explaining the pattern of updated priors in both segments. When $\xi > \phi(\bar{r}; \rho\tau) = 0.48$, as shown in Panel A, the sign-up population $p(\xi)$ remains at $(1 - \rho)\theta > 0$, which is the measure of tech-savvy high-type borrowers.

Our analysis hence generates a surprising comparative static result on the nonmonotonic relation between the equilibrium sign-up population $p(\xi)$ and ξ . Casual thinking might suggest that $p(\xi)$ decreases with ξ , as ξ captures the borrowers' concerns about data sharing. We show that this casual thinking captures some economics, but only partially. In the

scenario of small ξ , open banking allows fintech lenders to target high-type borrowers who are concerned about unfair pricing, and in fact this stigma effect goes a long way to prevent everybody from signing up for open banking, as discussed after Proposition 7. However, when the magnitude (ξ) of the preference shock is large, the opt-out incentive of low-type borrowers dominates the equilibrium credit quality inference, and eventually all tech-savvy high-type borrowers sign up for open banking in equilibrium.

Because ξ also serves as a proxy for the development stage of fintech lenders, our analysis suggests that the adoption of open banking might grow as the business model of fintech lenders under consideration improves. Our paper hence sheds some light on the economics behind the observed dynamics of open banking adoption. While the early lukewarm reception of open banking in the U.K. was often attributed to potential security-related privacy concerns caused by data sharing,³⁹ our analysis on the interaction between customer preferences and credit quality calls for a more careful examination of this conventional wisdom. In our model, nobody would sign up for open banking when fintech lenders still lack a clearly defined target market, with little potentially captured customers. Over time, the sign-up population grows once fintech lenders have established their niche markets with more and more captured customers.

4.4.2 Welfare: The perverse effect of open banking

Proposition 8 shows that open banking could make all borrowers worse off even though they control their own data, and at the same time lead to greater industry profit. This result follows irrespective of whether the data sharing concerns credit quality information as in Section 3, or some preference data that facilitates making exploitative loans as studied here.

To understand the result concerning borrower surpluses,⁴⁰ consider $\xi' = \phi(\bar{\tau}; \tau) + \epsilon$ so that from Proposition 6 we know that both types of borrowers suffer when sign-up is mandatory. But as illustrated in Panel B in Figure 3, which plots $\Delta V_i^{\xi, OB} \equiv V_i^{\xi, OB} - V_i^{\xi}$ (i.e., the impact of open banking on borrower surplus), this perverse effect of open banking prevails in the

³⁹Since the creation of the Open Banking Implementation Entity (OBIE) by in the U.K. in 2016, the industry has received little enthusiasm from consumers. For instance, see [Warwick-Ching \(2019\)](#), among others. The ongoing COVID-19 pandemic, which has forced consumers and financial institutions alike to recognize the essential nature of digital interactions, offers a great boost to the adoption of open banking. According to OBIE, over 2 million UK bank customers have connected their accounts to trusted third parties by the end of September 2020, up from 1 million in January 2020; and the actual number is likely higher as data was provided by the UK's nine largest banks (e.g., Barclays, HSBC, Santander, among others) and doesn't include challengers. See <https://bit.ly/3kTvbvg>.

⁴⁰The intuition of the lender profit result is similar to the one given right after Proposition 6.

shaded green area even when sign-up is voluntary.

The intuition for high-type borrowers is as follows. For tech-savvy high-type borrowers who choose to sign up, they suffer due to the fintech’s exploitative targeted loans facilitated by open banking, as shown in Proposition 6 for $\xi' = \phi(\bar{r}; \tau) + \epsilon < \tilde{\xi}$. Those who choose to opt out must be worse off as well—as suggested by the indifference equilibrium condition between opt-in and opt-out.

For high-type borrowers in the opt-out segment to receive worse treatment from lenders, the mechanism has to be the endogenous credit quality inference, i.e., a lower updated prior for credit quality τ_- . One can show this formally. The updated opt-out prior, i.e., $\tau_-(\xi')$ that solves $\xi' = \phi(\bar{r}; \tau_-(\xi'))$, must be below the prior τ (as shown in Panel A in Figure 8); that is to say, for the fintech to break even, we must have a lower updated prior for credit quality τ_- to compensate for a larger measure of captured borrowers.

Turning to low-type borrowers, those who opt-out from the open banking are worse off compared to the no-open-banking benchmark because of the lower opt-out updated prior τ_- . Again, the low-type but opt-in borrowers are worse off due to open banking, thanks to their indifference conditions—regardless of whether they are tech-savvy or not, opt-in or opt-out as in Panel B Figure 3.⁴¹

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. Two kinds of data sharing by borrowers are explored:

⁴¹The exact mechanism that hurts the low-type opt-in borrowers is as follows. Recall that before open banking the fintech with a sufficiently large number of captured borrowers lends aggressively ($m_f^\xi = 1$) upon seeing a good signal, benefiting the low type. With open banking and voluntary sign-ups, lender competition in the opt-out segment follows case (2) in Proposition 5; there, some endogenous $m_f^\xi < 1$ (i.e., the fintech might not lend) emerges to ensure the indifference condition of borrowers regarding their sign-up decisions, hurting the low-type borrowers.

one concerns their creditworthiness (i.e., information on lending cost), and the other their choice “privacy” (i.e., information on customer preferences).

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. In both scenarios, 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

<i>Notation</i>	<i>Definition and Meaning</i>	<i>Characterization</i>
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 bank, or fintech; strong, or weak	
$S_j \in \{H, L\}$	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	
\bar{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	
$F_j(r); \bar{F}_j(r)$	CDF of r_j ; survival function of $F_j(r)$	$\bar{F}_j(r) = 1 - F_j(r)$
λ_j	The mass point of $F_j(r)$ at \bar{r}	$\lambda_j = \lim_{r \uparrow \bar{r}} \bar{F}_j(r)$
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 4	

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 $r \uparrow \bar{r}$, at least one of $\bar{F}_s(r)$ and $\bar{F}_w(r)$ will be zero since it is impossible that both distributions have a mass point at $r = \bar{r}$ in equilibrium. Suppose $\bar{F}_w(\bar{r}) = 0$. 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 $\bar{F}_w(r) = \bar{F}_s(r) = 1$, 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 $\pi_s > \pi_w = 0$. \square

A.3 Proof of Proposition 1

Proof. We know the strong lender's distribution is $\bar{F}_s(r) = \phi(r)$. From $\bar{F}_s(\underline{r}) = 1$, we solve $\underline{r} = (1 - x_w)/\tau$, which is less than \bar{r} given condition (1). The size of F_s 's mass point is $\lambda_s = \phi(\bar{r})$, 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 $r = \bar{r}$ in (3) yields $1 - m_w = \phi(\bar{r})$. Finally, $\bar{F}_w(r)$ is solved from (3). \square

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 $r \in [\underline{r}, \bar{r}]$, 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

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

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 $\bar{F}_w(r)$ 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). \square

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

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

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

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

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:

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

and

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

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

$$\phi_-(\bar{r}) > \phi_+(\bar{r}). \quad (29)$$

Using the expression for the ϕ function, we have

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

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

$$\underline{r}_- > \underline{r}_+. \quad (30)$$

Then from (29), (30) and V_h defined in (9), we derive

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

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. \square

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 $V_l(x_f, x_b, \tilde{r})$ as follows:

$$V_l(x_f, x_b, \tilde{r}) = \begin{cases} 1 - x_b \left[x_f + (1 - x_f) \frac{x_b}{\frac{\tilde{r}}{1-x_f} - (1-x_b)} \right], & \text{if } \tilde{r}\bar{r} \geq 1 - x_f, \\ 1 - x_b, & \text{if } 1 - x_b < \tilde{r}\bar{r} < 1 - x_f, \\ (1 - x_b) m_b, & \text{if } \tilde{r}\bar{r} = 1 - x_b, \\ 0, & \text{if } \tilde{r}\bar{r} < 1 - x_b. \end{cases} \quad (31)$$

(We have ignored δ , the size of the nonmonetary 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:

$$\tau_-(\sigma_l) = \frac{\rho\tau}{1 - (1 - \rho)\sigma_l} \leq \tau_+(\sigma_l) = \frac{\tau}{\sigma_l}. \quad (32)$$

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

$$V_l(x_f, x_b, \tau_-(\sigma_l)) = V_l(x_b, x'_f, \tau_+(\sigma_l)). \quad (33)$$

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 (33) 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 (33) 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 (33) is smaller when $\sigma_l = 0$. Moreover, the left-hand side $V_l(x_f, x_b, \tau_-(\sigma_l))$ as defined in (31) 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 $V_h(x_f, x_b, \rho\tau) < V_h(x_b, x'_f, \infty) = \bar{r}$. 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 (33) depends on how many lenders are active in the opt-out market. Let us first introduce two pieces of notation: let σ'_l solve

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

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

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

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 $\rho\tau\bar{r} < 1 - x_f$, and $\sigma''_l \in (0, 1)$ is well defined if $\rho\tau\bar{r} < 1 - x_b$, and $\sigma''_l < \sigma'_l$ in the latter case. More explicitly, we have

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

We need to deal with three cases separately:

(i) When $\rho\tau\bar{r} \geq 1 - x_f$, 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 (31). Then (33) becomes

$$x_b[x_f + (1 - x_f)\frac{x_b}{\frac{\tau_-(\sigma_l)\bar{r}}{1-x_f} - 1 + x_b}] = x'_f[x_b + (1 - x_b)\frac{x'_f}{\frac{\tau_+(\sigma_l)\bar{r}}{1-x_b} - 1 + x'_f}], \quad (34)$$

where $\tau_-(\sigma_l)$ and $\tau_+(\sigma_+)$ are defined in (32).

(ii) When $1 - x_b < \rho\tau\bar{r} < 1 - x_f$, 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,

$$x_b = x'_f[x_b + (1 - x_b)\frac{x'_f}{\frac{\tau_+(\sigma_l)\bar{r}}{1-x_b} - 1 + x'_f}]. \quad (35)$$

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 (34) 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 $\rho\tau\bar{r} \leq 1 - x_b$, 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 (31). 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 (34). 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 (35). 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. \square

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 $\tau_- \bar{\tau} = 1 - x_f$. Given our assumption $\tau \bar{\tau} > 1 - x_f$, 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 $\tau_- \bar{\tau}$ 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 $\tau_- \bar{\tau} = 1 - x_f$, one can check that $\frac{V_l(x_f, x_b, \tau_-)}{\delta} = 1 - x_b$. Then (15) requires

$$x_b = x'_f \left(x_b + (1 - x_b) \frac{x'_f}{\frac{\bar{\tau} \tau_+}{1 - x_b} - 1 + x'_f} \right). \quad (36)$$

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 (36) exceeds x_b when $x'_f = 1$, and given that $\bar{\tau} \tau > 1 - x_b$, 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

$$\frac{n_+}{1 + \tau_+} + \frac{n_-}{1 + \tau_-} = \frac{1}{1 + \tau}. \quad (37)$$

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

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

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

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

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 (37).

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 (37), 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. \square

A.10 Proof of Proposition 5

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

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

From Equation (17), if $\xi < \phi(\bar{r})$, 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 (18) yields:

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

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

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

The fintech has the same strategy as in the baseline (the bank has the same indifference condition

19): upon seeing a good signal, it makes an offer with probability $m_f^\xi = 1 - \phi(\bar{r})$, and the offer randomizes over $[\underline{r}^\xi, \bar{r}]$ according to

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

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

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

where the second term in the curly bracket corresponds to the ξ -event in which there is only one lender. Plugging in $\bar{F}_j^\xi(r)$ 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

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

In the $1 - \xi$ event, the equilibrium differs from baseline equilibrium only in bank pricing $\bar{F}_b^\xi(r)$, 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 $m_f^\xi = 1 - \phi(\bar{r})$).

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

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

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

Similar to [Varian \(1980\)](#), the unique equilibrium is a mixed-strategy on common support $[\underline{r}^\xi, \bar{r}]$. Equation (17) shows that when $\xi > \phi(\bar{r})$, the fintech makes positive profit (one feasible strategy is to always offer $r = \bar{r}$ 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 $j \in \{b, f\}$.⁴²

⁴²The 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.

The fintech's indifference condition is

$$r \in (\underline{r}^\xi, \bar{r}) : \pi_f^\xi = p_{HH} \left[\xi + (1 - \xi) \bar{F}_b^\xi(r) \right] [\mu_{HH}(r + 1) - 1] - p_{LH}. \quad (38)$$

Evaluating (38) at $r = \bar{r}$ yields the fintech's profit

$$\pi_f^\xi = \xi \cdot \frac{\tau \bar{r} - (1 - x_f)}{1 + \tau} - (1 - \xi) \cdot \frac{x_b(1 - x_f)}{1 + \tau}, \quad (39)$$

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

$$\underline{r}^\xi = \xi \bar{r} + (1 - \xi) \frac{(1 - x_b)(1 - x_f)}{\tau} > \underline{r}. \quad (40)$$

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

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

The bank's indifference condition is

$$r \in (\underline{r}^\xi, \bar{r}) : \pi_b^\xi = (1 - \xi) \left\{ p_{HH} \bar{F}_f^\xi(r) [\mu_{HH}(r + 1) - 1] - p_{HL} \right\}. \quad (41)$$

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

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

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

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

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

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

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

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,

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

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

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

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. \square

A.11 Proof of Proposition 6

Proof. 1. When $\xi \leq \phi(\bar{r})$, it is straightforward to check that $V_h^{\xi, OB}(\tau) < V_h^\xi(\tau)$ in (20) 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 (23) and (26), we have

$$V_l^\xi = \delta(1 - \xi)(1 - x_b x_f) + \delta\xi(1 - x_f) > (1 - \xi)V_l(\tau) + \delta\xi(1 - x_f) = V_l^{\xi, OB}(\tau), \quad (42)$$

where the inequality holds as $\delta(1 - x_b x_f)$ is greater than $V_l(\tau)$ in (10). (The equality will hold if $\tau \rightarrow \infty$.)⁴³ 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

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

⁴³In the knife edge case, open banking may hurt or benefit low-type depending on the equilibrium $m_f^\xi \in [1 - \phi(\bar{r}), 1]$.

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 (24) and (39) it is immediate to see that the fintech benefits from open banking; while the bank suffers as

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

where $\underline{r}^\xi > \underline{r}$ as shown in Proposition 5. \square

A.12 Proof of Proposition 7

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

A.13 Proof of Proposition 8

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 $\tilde{\xi} \in (\phi(\bar{r}; \tau), \phi(\bar{r}; \rho\tau))$ 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 $\phi(\bar{r}; \tau_- = \tau \frac{\rho + (1-\rho)(1-\sigma_h)}{\rho + (1-\rho)(1-\sigma_l)}) = \xi$, σ_l must be smaller if $\sigma_h < 1$ than when $\sigma_h = 1$. When $\sigma_h = 1$, we have $\sigma_l = \frac{1 - \tau_- \rho}{1 - \rho}$, 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 $\xi \in [\phi(\bar{r}; \tau), \tilde{\xi}]$. 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,

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

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

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

$$\begin{aligned}\pi_b^{\xi, OB} &= \pi_{b+}^{\xi, OB} + \pi_{b-}^{\xi, OB} = \underbrace{n_+ (1 - \xi) \frac{x_b - x_f}{1 + \tau_+}}_{=\pi_{b+}^{\xi, OB}} + \underbrace{n_- (1 - \xi) \frac{x_b - x_f}{1 + \tau_-}}_{=\pi_{b-}^{\xi, OB}} = (1 - \xi) \frac{x_b - x_f}{1 + \tau}, \\ \pi_f^{\xi, OB} &= \pi_{f+}^{\xi, OB} + \underbrace{\pi_{f-}^{\xi, OB}}_{=0} = \xi [\theta (1 - \rho) \sigma_h \bar{r} - (1 - \theta) (1 - \rho) \sigma_l (1 - x_f)];\end{aligned}$$

while their profits before open banking are

$$\begin{aligned}\pi_b^\xi &= (1 - \xi) \left[\xi \frac{\bar{r}\tau}{1 + \tau} - \xi \frac{1 - x_b}{1 + \tau} - (1 - \xi) \frac{(1 - x_b)x_f}{1 + \tau} \right], \\ \pi_f^\xi &= \xi \theta \bar{r} - \xi (1 - \theta) (1 - x_f) - (1 - \xi) (1 - \theta) x_b (1 - x_f).\end{aligned}$$

We hence have that

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

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. \square

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.⁴⁴

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, said⁴⁵

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

⁴⁴In 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 Banking, APIs, and Liability Issues](#)" by Rich Zukowsky (2019).

⁴⁵See [link](#).

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.⁴⁶ 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.

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.

⁴⁶Of 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.

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 \bar{r} in their supports;*
2. *they have no gaps in their supports;*
3. *one of them can have a mass point at \bar{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 $\max\{\bar{r}_w, \bar{r}_s\} < \bar{r}$. If $\bar{r}_w \neq \bar{r}_s$, then for the lender with the higher upper bound, offering an interest rate slightly above its upper bound will be a profitable deviation. If $\bar{r}_w = \bar{r}_s$, 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, $\bar{r}_w < \bar{r}$ and $\bar{r}_s = \bar{r}$. Then the support of F_s would have a gap in (\bar{r}_w, \bar{r}) since any interest rate in this interval is dominated by \bar{r} . But this is impossible in equilibrium since for at least one lender offering an interest rate slightly above \bar{r}_w would be a profitable deviation. This proves $\bar{r}_w = \bar{r}_s = \bar{r}$.

(ii) Suppose that, say, the support of F_s has a gap $(r_1, r_2) \subset [\underline{r}, \bar{r}]$. 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 $\tilde{r} \in (\underline{r}, \bar{r})$. 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 $0 < \varepsilon < \bar{r} - \tilde{r}$. 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 \bar{r} . \square

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}) is⁴⁷

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

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 $r = \bar{r}$, 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),

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

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

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

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

⁴⁷We 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

$$x_f \nearrow x_b \nearrow x_{f'} \equiv x. \quad (43)$$

We assume that $\delta \rightarrow 0$: 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

$$\pi_b(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \bar{F}_f(r)\right]^2}_{\text{winning both competitors}} [\mu_{HHH}(1+r) - 1] \quad (44)$$

$$- 2 \underbrace{p_{HHL}}_{\text{b and one f make mistakes}} \underbrace{\left[1 - m_f + m_f \bar{F}_f(r)\right]}_{\text{bank wins over competing f}} - p_{HLL} \quad (45)$$

Fintech's indifference condition

$$\pi_f(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \bar{F}_f(r)\right] \bar{F}_b(r)}_{\text{winning both competitors}} [\mu_{HHH}(1+r) - 1] \quad (46)$$

$$- \underbrace{p_{LHH} \left[1 - m_f + m_f \bar{F}_f(r)\right] - p_{HHL} \bar{F}_b(r) - p_{LHL}}_{\text{fintech and its one competitor make mistake}}. \quad (47)$$

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

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

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

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

With three players, there is a new event: one of the competitors makes the same mistake and may burdern 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 $\delta \rightarrow 0$,

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

After mandatory open banking, there are three equilibria, but borrower surplus are equivalent when $\delta \rightarrow 0$.⁴⁸ For the calculation, we use the asymmetric equilibrium. Let m' denote the probability that fintech makes an offer after mandatory open banking, then

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

Under the parameter setting (43), h -type surplus depends on the relative relationship between m' and $m_f (2 - m_f + x m_f)$.

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

⁴⁸In the symmetric equilibrium, withdrawing with probability $1 - m$ loses the NPV from h type

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

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

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

following relationships between m_f , m' , and x :

$$\begin{aligned}\pi_b &= p_{HHH} (1 - m_f)^2 [\mu_{HHH} (1 + \bar{r}) - 1] - 2p_{HHL} (1 - m_f) - p_{HLL} \rightarrow 0 \\ \Rightarrow (1 - m_f)^2 \frac{\bar{r}}{r} - 1 + (1 - x) m_f (2 - m_f + m_f x) &\rightarrow 0;\end{aligned}\tag{48}$$

$$\begin{aligned}\pi_f &= p_{HH} (1 - m') [\mu_{HH} (1 + \bar{r}) - 1] - p_{HL} = 0 \\ \Rightarrow (1 - m') \frac{\bar{r}}{r} - 1 + m' (1 - x) &= 0.\end{aligned}\tag{49}$$

We can rearrange the above two equations (r are the same as $x_f \nearrow x_b \nearrow x_f \equiv x$),

$$\underbrace{(1 - m_f)^2 \left[\frac{\bar{r}}{r} - (1 - x) \right] - x + m_f^2 x (1 - x)}_{LHS \text{ from (48)}} \rightarrow \underbrace{(1 - m') \left[\frac{\bar{r}}{r} - (1 - x) \right] - x}_{LHS \text{ from (49)}} = 0,$$

which implies

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

Plug this back into (48) and (49), we have

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

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 7

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 $\{m_{j+}^{\xi, OB}, \lambda_{j+}^{\xi, OB}, F_{j+}^{\xi, OB}\}$ and $\{m_{j-}^{\xi, OB}, \lambda_{j-}^{\xi, OB}, F_{j-}^{\xi, OB}\}$ respectively for borrowers who opted in and who opted out.

Contrary to Subsection 4.3.1, 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 5; 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 27 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 5. Then for the high-type to be willing to sign up,

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

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 (21) and (26), 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 5. If $\xi < \phi(\bar{r}; \tau_-)$, the competition follows Case 1 in Proposition 5, 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 5. 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: $\xi > \phi(\bar{r}; \rho\tau)$

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 $\xi > \phi(\bar{r}; \rho\tau) \geq \phi(\bar{r}; \tau_-)$: lender competition for borrowers who did not sign up always follows Case 3 in Proposition 5.

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 $\xi\bar{r}$, and is smaller than that before open banking, $(1-\xi)\mathbb{E}\left[\min\left\{r_b^\xi, r_f^\xi\right\}\right] + \xi\mathbb{E}\left[r_f^\xi\right]$:

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

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

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

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

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 $\xi > \phi(\bar{r}; \tau_-)$, and lenders compete for the opt-out segment following Case 3 in Proposition 5, 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 $\xi > \phi(\bar{r}; \tau) \geq \phi(\bar{r}; \tau_-)$. 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

$$\tau_- = \frac{1 - x_f}{\bar{r}} \left(\frac{x_b}{\xi} + 1 - x_b \right). \quad (50)$$

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 (25) and (26) 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.⁴⁹ $V_{i,-}^{\xi, OB}(\tau_-) = V_{i,+}^{\xi, OB}(\tau_+)$, $i = h, l$. Hence, we have⁵⁰

$$\phi_+(\bar{r}) = \frac{2x_b + (1 + \xi)(1 - x_b) - \sqrt{[2x_b + (1 + \xi)(1 - x_b)]^2 - 4\xi(x_b + (1 - x_b)\xi)}}{2(x_b + (1 - x_b)\xi)}, \quad (52)$$

⁴⁹Equilibrium $m_{f-}^{\xi, OB}$ is well defined and unique. The low-type's indifference condition is equivalent to

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

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 $\phi_-(\bar{r})(\xi + (1 - \xi)x_b) > (1 - \xi)x_b \underbrace{\phi_+(\bar{r})}_{< \phi_- = \xi}$, 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.

⁵⁰It follows that $\phi_+(\bar{r})$ satisfies the following quadratic equation,

$$(x_b + (1 - x_b)\xi) \phi_+^2 - [2x_b + (1 + \xi)(1 - x_b)] \phi_+ + \xi = 0. \quad (51)$$

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

and

$$m_{f-}^{\xi,OB} = 1 - \frac{(1-\xi)x_b\phi_+(\bar{r})}{\xi + (1-\xi)x_b}. \quad (53)$$

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

$$\sigma_h = \frac{\frac{\tau_+}{\tau_-} - \frac{\tau_+}{\tau}}{(1-\rho)\left(\frac{\tau_+}{\tau_-} - 1\right)} \text{ and } \sigma_l = \frac{\frac{\tau}{\tau_-} - 1}{(1-\rho)\left(\frac{\tau_+}{\tau_-} - 1\right)}, \quad (54)$$

where τ_- is determined in (50) and τ_+ is determined by (52) and (6). Note that $\frac{\partial}{\partial \tau_-} \phi(\bar{r}; \tau_-) < 0$ implies that $\tau_- < \tau < \tau_+$ for $\xi > \phi(\bar{r}; \tau)$ and $\phi(\bar{r}; \tau_-) = \xi$. 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., $\xi < \phi(\bar{r}; \tau)$) 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 (53).

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

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

Hence, high-type borrowers strictly prefer to sign up (the case in point 2), and $\sigma_h = 1$ (at the same time, $\sigma_l \rightarrow 0$). As at the other endpoint $\xi = \phi(\bar{r}; \tau)$, we have $\tau_- = \tau$ and thus $\sigma_h = \sigma_l = 0$. By continuity, there exists a $\tilde{\xi} \in (\phi(\bar{r}; \tau), \phi(\bar{r}; \rho\tau))$ 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 7

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 $\phi(\bar{r}; \tau_-) = \xi$ implies that $\frac{\bar{r}\tau_-}{1-x_f} - 1 = \frac{\xi x_b}{1-\xi}$, so we have

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

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

$$1 - \frac{\phi(\bar{r}; \tau_-)}{\phi(\bar{r}; \tau)} + (1 - \rho) \sigma_l = \frac{(\tau - \tau_-)}{\underbrace{(\tau_+ - \tau_-)(\bar{r}\tau_- - (1 - x_b)(1 - x_f))}_{\text{positive}}} (2\bar{r}\tau_- - \bar{r}\tau_+ - (1 - x_b)(1 - x_f)). \quad (55)$$

Hence the question boils down to the sign of the last parenthetical term in Eq. (55). Notice that while $\tau_- = \tau$ is continuous at $\xi = \phi(\bar{r}; \tau)$, $\tau_+ = \tau \frac{\sigma_h}{\sigma_l}$ typically jumps upward at $\xi = \phi(\bar{r}; \tau)$ from the left. So it is nontrivial to show that the total financial sector gains even when in the neighborhood of $\xi = \phi(\bar{r}; \tau)$.

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

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

We then try to ensure that $\tau_+ < 2\tau_- - \frac{(1-x_b)(1-x_f)}{\bar{r}}$ (so that the last parenthetical term in Eq. (55) is positive), by checking the sign of $Q\left(\tau_+ = 2\tau_- - \frac{(1-x_b)(1-x_f)}{\bar{r}}\right)$, which equals

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

Because $Q(\cdot)$ is quadratic and opens upward, and we take the larger solution (see footnote 50), to ensure $Q\left(\tau_+ = 2\tau_- - \frac{(1-x_b)(1-x_f)}{\bar{r}}\right) > 0$, we need

$$M(\xi) \equiv 2(1 - x_b)\bar{r}\tau_-(\xi) - (5 - x_b)(1 - x_b)(1 - x_f) + (1 - x_f) > 0$$

for $\tau_-(\xi)$ when $\xi \in [\phi(\bar{r}; \tau), \tilde{\xi}]$. (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 $\xi = \phi(\bar{r}; \tau)$, $\tau_-(\xi) = \tau$, so we require that (recalling $\rho\bar{r}\tau \geq 1 - x_f$ in (27))

$$\frac{2}{\rho}(1 - x_b) - (5 - x_b)(1 - x_b) + 1 > 0. \quad (56)$$

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

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

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

$$2(1 - x_b) \frac{\tau_+(\tilde{\xi})}{\tau_+(\tilde{\xi}) - (1 - \rho)\tau} - (5 - x_b)(1 - x_b) + 1 > 0, \quad (57)$$

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

In sum, (56) and (57) guarantee that the financial sector gains after open banking when $\xi \in [\phi(\bar{r}; \tau), \tilde{\xi}]$ (note, these conditions are also necessary if $\rho \bar{r} \tau = 1 - x_f$ and for sufficiently large x_j 's). \square