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

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Abstract

Open banking facilitates data sharing consented by customers who generate the data, with a regulatory goal of promoting competition between traditional banks and challenger fintech entrants. We study lending market competition when sharing banks' customer transaction data enables better borrower screening 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 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 the rapidly evolving information and digital technology. Customer data—instead of being zealously kept within individual organizations or institutions in an isolated fashion—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,” Second Payment Services Directive (PSD2) envisions enabling customers to voluntarily share their financial data with other entities, via application programming interfaces, or APIs. Indeed, PSD2, by mandating European banks to 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 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 not a European initiative anymore. In the U.S., for decades traditional banks have used credit reports as the maintools to determine who gets a loan. However, credit reports generally reflect a person’s borrowing history, leaving customers with cash or debit cards only unserved. In 2019, FICO, Experian, and Finicity jointly launched a pilot program on “UltraFICO” via which

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

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

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

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 or no credit histories. A natural question is: why cannot 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 basically open banking.[5]

We provide a brief overview of Open Banking, including its core API technology and the current status of business practice in Appendix A.1, with the theme of credit market development and competition given the focus of paper. Borrowers' information sharing—especially their bank account data—through open banking is instrumental for fintech firms (say, LendingClub at the U.S. or MarketPlace at the U.K.) who specialize in small business and consumer lending; Dan Kettle at Pheabs, a U.S. fintech company, argues that[6]

> 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 other high cost loans, these will raise warning flags on our system and we know that 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—have profound implications on credit market competition and welfare. To the best of our knowledge, our paper is the first to study this question theoretically. Although the role of information technology has been extensively studied in the banking literature, our paper emphasizes that, different from 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 interesting questions regarding the welfare implications of open banking.

More specifically, our model considers a traditional bank and a fintech lender in competition with each other. They conduct independent but imperfect creditworthiness tests before making loan offers to borrowers. Each borrower can have a high or low credit quality, and the test yields a binary signal of their credit quality. This framework is based on Broecker (1990) and has been

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

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

[6] `https://www.accountancyage.com/2021/02/22/open-banking-is-revolutionary-but-will-it-take-off/`

widely used to study lending market competition as we will discuss later. 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 that has a better screening ability and so faces a less severe winner's curse earns a positive profit in expectation, while the other one with a weaker screening ability earns a zero profit and sometimes declines to extend an offer to a borrower 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 a 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), but much more advanced data analysis algorithms; without enough data, however, 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 via 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. Besides, we also assume there exist non-tech-savvy borrowers who face infinite sign-up costs (e.g., because they do not know how to use the new technology or have strong privacy concerns) and hence always opt out from open banking.

Section 3 examines credit-quality data sharing. Once the fintech has an 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.[7] The improvement of the fintech's screening ability has two effects: First, as the fintech now can better identify a borrower's true type, it helps high credit quality borrowers but hurts low credit quality borrowers. This is a standard "information effect." Second, it also affects the extent of winner's curse that each lender faces, and so the degree of lending competition. This "strategic effect" can go 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.

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

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 from happening? After all, borrowers will not act against their own interest. Our analysis with voluntary sign-up decisions provides a negative answer to this question. We show that there exists a range of parameters under which high-type borrowers opt in, some low-type borrowers opt out, and all borrowers are strictly worse off compared to the regime 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 perverse effect of open banking in which all borrowers might hurt even with voluntary sign-ups. In practice, 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 threat than opportunity.[8] This is especially true for fintech challengers who are offering competing services and have gained valuable new data via their modern customer relationships and are equipped with better data analysis technology, and this is exactly the situation where the perverse effect of open banking is more likely to arise. We also highlight that the adverse credit quality inference of opting-out, which is driven by the very fact that high-type borrowers have more incentives to share their data to lenders, is the key to generate this perverse effect.

Section 4 studies data sharing on customer preferences. We assume that borrowers are subject to some random shocks under which they can only take the fintech's loan. For instance, they happen to need a quick loan and only the fintech can process with "immediacy";[9] or they have reached the bank's borrowing limit and so can only resort to the fintech. Open banking, with the aid of big data technology that can integrate, say, borrowers' social data and digital footprints together with their bank account information, allows the fintech to identify these "preference events." (For a clean analysis we shut down the channel of an enhanced credit screening ability for the fintech studied before.) Accordingly, the fintech can "target" on some borrowers by performing precision marketing, or in other words, "delivering the right offer at the right time to the right customer." The borrowers, once hit by the preference shocks, resemble the "captured" consumers in Varian (1980) who consider only one seller's offer.

When the probability of preference events is sufficiently low, the small pool of captured borrowers is not enough to compensate the loss from the winner's curse for the fintech lender, who has an inferior screening ability. Similar to the baseline model, the fintech hence earns a zero profit in equilibrium and sometimes does not make offers to borrowers with a good signal. (This differs

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

[9] Transaction 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"—e.g., borrowers traveling abroad need loans in foreign currencies on the spot, or consumers on e-commerce platforms with impulse purchase needs.

from Varian (1980) where winner's curse is absent and any firm with some captured consumers must earn a positive profit.) Open banking allows the fintech to identify borrowers in preference events, to whom the fintech always extends an offer upon a good signal but at a monopoly interest rate. If there were no credit quality inference from sign-up decisions, high-type borrowers would opt out to avoid paying a predatory interest rate, while the opposite holds for the low type who repay much less often and hence care little about the interest rate. Due to this stigma effect of associating signing up with low credit quality, nobody signs up in equilibrium after open banking.

The results are rather different for a large probability of preference events. With many potential captured borrowers, the fintech now earns a positive profit and always makes an offer upon a good signal. This is particularly attractive to the low-type who only care about the chance of getting a loan—in fact, they never sign up for open banking to reveal preference events. Opting-in leads to a favorable credit quality inference, and high-type borrowers sign up in equilibrium.[10] Piecing this together with the previous case, we predict, perhaps counter-intuitively, a rising sign-up population or widespread open-banking adoption together with the growing captured borrowers by the fintech business.

In terms of the impact of open banking regarding the preference based privacy on borrower welfare, we have a similar result as in the case of data sharing on credit quality. That is, all borrowers may suffer from 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 privacy events; those who do not suffer due to an unfavorable credit quality inference.

Through a normative analysis within a canonical economic framework, our paper highlights that the welfare implication of open banking with informed consent, and calls for more future studies on understanding the implications of "sharing" in open data economy.

Related Literature

Lending market competition with asymmetric information. Our paper is built on Broecker (1990), which 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.[11] Hauswald and Marquez (2003) study the competition between an inside bank who can conduct credit screening and an outside bank who 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. When open bank-

[10] Low-type borrowers who opt out from open banking are still served because of the existence of borrowers who never sign up but could be of high type.

[11] Lending market competition with asymmetric screening abilities is related to common-value auctions with asymmetrically informed bidders. The early papers include Milgrom and Weber (1982) and Engelbrecht-Wiggans, Milgrom, and Weber (1983); later papers such as 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). The common-valuation auction literature suggests that reducing the more-informed bidder's information advantage tends to intensify competition and improve the seller's revenue, a result emerging in our baseline model as well.

ing facilitates sharing data on customer credit quality, it has some connection to the information spillover effect studied in Hauswald and Marquez (2003).

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 the control of whether to share their data, and their sign-up decision itself can potentially reveal further creditworthiness information. Third, open banking can also reveal non-credit 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; this idea was explored by Sharpe (1990).[12] In our model, information asymmetry before open banking exists for the same reason: traditional banks own the customer data that fintech lenders have no access to, so that even if fintech lenders have a better data processing algorithm, they screen borrowers less accurately.

Our paper is also related to the literature on credit information sharing among banks; e.g., Pagano and Jappelli (1993) and Bouckaert and Degryse (2006).[13] More broadly, lending market competition with asymmetric information is important for studying many issues such as capital requirement (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), etc.

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.[14] 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. On studies that support the notion of a competition relationship between fintech and bank in our paper, Fuster, Plosser, Schnabl, and

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

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

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

Vickery (2019) examine the mortgage market and provide evidence that fintech lenders' technology advantage increases origination efficiency: the automated fintech lending system results in faster processing and more elastic response to changes in borrower demand. 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 non-fintech 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.[15]

On the theoretical font, Parlour, Rajan, and Zhu (2020) is closely related to our work by studying a bank that operates in both payment service and credit (loan) markets; the vertically integrated bank competes with stand-alone fintechs on payment services as well as stand-alone fintech lenders. Parlour, Rajan, and Zhu (2020) stress that customers' payment services provide information about their credit quality, and this payment-service information is equally useful for two lenders in their paper. In contrast, in our model this payment-service information can improve the two lenders' screening technologies differently, given their different data analysis algorithms. This heterogeneous information effect drives our non-trivial welfare result.[16]

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. Recent research suggests that the market equilibrium consequence of consumer privacy choices is highly context dependent. For example, in a general equilibrium setup Jones and Tonetti (2020) argue that consumer data ownership often leads to broader data usage than in the case of firm ownership, improving welfare thanks to the non-rivalry of data use.[17] By studying consumer privacy choices in the lending market, our paper highlights the equilibrium credit quality inference from consumers' sign-up decisions in open banking. Aridor, Che, and Salz (2020) offer evidence that this type of inference 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.

[15]By studying the mortgage market, Buchak, Matvos, Piskorski, and Seru (2018) argue that regulation and technology advancement contributed to the significant growth of fintech lenders. Tang (2019) uses a regulatory change that contracts bank credit as an exogenous shock and show that P2P platforms substitute with bank in the consumer credit market.

[16]In their base model, there is no equilibrium credit quality inference (which plays the key role in our analysis), because whether a consumer switches the payment service to fintechs is driven by her bank-affinity preference that is independent of her credit quality type. 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.

[17]Ichihashi (2020) considers a multi-product monopoly problem where consumers choose whether to share data about their preferences, which can be used by the seller for both product recommendations and price discrimination. Liu, Sockin, and Xiong (2020) examine the implications of consumer privacy when there is both a normal consumption good and a temptation good; data sharing shapes sellers' marketing schemes for reaching target consumers, which improve the efficiency of the normal good but also induce some behaviorally biased consumers to overconsume the temptation good. Liu, Sockin, and Xiong (2020) emphasizes the difference between two consumer privacy regulations, namely GDPR in EU (opt-out as the default choice) and CCPA in California (opt-in as the default choice).

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.2 provides a detailed list of the notation used in this paper. All proofs are relegated to the Appendix.

2.1 Borrowers

There is a continuum of risk-neutral borrowers of measure one. Each is looking for a loan that is normalized to be 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 loan, and the rest $1-\theta$ of them are low-type (l) and always default. Each borrower's type is that borrower's private information, but the type distribution is publicly known. Let

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

be the likelihood ratio of high-type over low-type borrowers in the population, which represents the average credit quality of borrowers (perhaps summarized by their credit scores). We also 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 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 we assume that the utility from consuming the product is sufficiently high for each type of consumer,[18] but the interest rate is capped at $\bar{r}$ either due to interest rate regulation (e.g., usury laws) that prohibits excessively high rates of interest,[19] or because of some exogenous outside options.

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

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

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

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 *s*trong lender (denoted by s) and the other a *w*eak 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, which differ in their screening abilities.

Following Broecker (1990), we assume that each lender receives an independent and private signal of a borrower's type via a 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 will 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 will observe a low signal L more likely than the weak lender. That is, the strong lender has a better screening ability. The two lenders' screen abilities are publicly known. Notice that we have a "bad-news" signal structure, i.e., a bad signal perfectly reveals a borrower to be the low type while a good signal is inconclusive.[20] In the following, we use high (low) signals and good (bad) signals exchangeably.

After receiving their private signals, the lenders update their beliefs about the borrower's type and make their loan offers $r_j \in [0, \overline{r}]$ (if any) simultaneously. The borrower chooses the offer with the lower interest rate.[21] (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.[22]

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

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

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

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

[20] Chu and Wei (2021) study a similar setting with asymmetric lenders but a different information structure.

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

[22] When it comes to open banking applications, we could alternatively assume that the fintech lender has a higher financing cost than the traditional bank. The fintech's disadvantageous position in financing cost is a well-known empirical regularity, because of their lack of cheap and stable funding sources like deposits. However, considering asymmetric funding costs only complicates the analysis without adding significant economic insight given our focus.

This is easier to hold when there are more high-type borrowers in the population, i.e., a higher τ, or when the screening ability is better. This assumption, together with the bad-news signal structure, implies that in our model the only mistake lenders may make is lending to a low-type borrower.

Finally, we assume that any borrower of type i obtains a non-monetary benefit δ_i just from getting a loan. For high-type borrowers, they are left with some endogenous rent thanks to lender competition. We hence normalize δ_h to 0 for convenience as δ_h plays no role in our subsequent analyses. We, however, set $\delta_l = \delta > 0$. In the context of small business loans, δ can be interpreted as the control rent of entrepreneurs from non-pledgeable income (see, for instance, Tirole, 2010), so that low-type borrowers who never succeed still care about the likelihood of getting a loan. This makes low-type borrowers' welfare meaningful, and for our applications we think about the control rent δ as relatively small.[23]

2.3 Equilibrium Characterization

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

2.3.1 Preliminary analysis

Let

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

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

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

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

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

the probability that the strong lender observes a good signal but the weak one 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 that the stronger lender observes a bad signal but the weak one observes a good signal. 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 a flavor of common-value auctions. A lender wins a borrower if it offers a better interest rate than its rival, or if the rival does not make an offer at all, which happens when it sees a bad signal. Hence, winning the borrower brings some bad news—a winner's curse. To illustrate, suppose that the two lenders offer the same interest rate

[23] For the interpretation of consumption loans, δ then represents the low-type borrowers' utility from consuming the product. Following the discussion in footnote 18, we only need $\delta \geq 0$ so δ can be arbitrarily small.

$r \leq \overline{r}$. Then the strong lender's profit, for instance, is

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

When both observe a good signal from a borrower (which occurs with probability p_{HH}), the strong lender wins the borrower with probability 1/2; when the strong lender observes a good signal but the weak one observes a bad signal (which occurs with probability p_{HL}), the former wins for sure, but in that case the borrower must be of low type and so will never repay the loan.

Due to this winner's curse, it is easy to see that in our model there is no pure-strategy equilibrium.[24] We introduce some notations to characterize the mixed-strategy equilibrium that arises. Let m_j, $j \in \{s, w\}$, be lender j's probability that it 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; as shown in the online Appendix, the two lenders' distributions must share the same support with common lower bound $\underline{r}$ (which will be specified below) and upper bound $\overline{r}$. For our subsequent analysis, it is more convenient to use the survival function $\overline{F}_j(r) \equiv 1 - F_j(r)$. Let π_j be the lender j's equilibrium (expected) profit.

In a mixed-strategy equilibrium, the strong lender's indifference condition, when $r \in [\underline{r}, \overline{r}]$, is

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

When the strong lender offers interest rate r upon seeing a good signal, there are two possibilities: if the weak lender also observes a good signal (which occurs with probability p_{HH}), the strong lender wins if the weak one does not make an offer (which occurs with probability $1 - m_w$) or if the weak one makes an offer but its interest rate is above r (which occurs with probability $m_w \overline{F}_w(r)$); 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 make a loss of 1. Similarly, the weak lender's indifference condition is

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

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

This is because the weak lender faces a higher lending cost due to its more severe winner's curse (i.e., $p_{LH} > p_{HL}$). Given that there is no product differentiation, only the lender with the

[24] 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 and make a nonnegative profit, then the first portion in (2) must be strictly positive, in which case each lender will have a unilateral incentive to undercut its opponent. It is also routine to show that the mixed-strategy equilibrium behaves well.

lower cost makes a positive profit. As we will see below, the strong lender's profit actually equals $p_{LH} - p_{HL} = (1-\theta)(x_s - x_w)$.

2.3.2 Mixed-strategy competition equilibrium

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

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

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

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

which is $\overline{F}_s(r)$ solving (5). Note that $\phi(r)$ depends on primitive parameters x_w, x_s, and τ, and $\phi(\overline{r}) \in (0,1)$ (Assumption (1) implies that $1-\phi(\overline{r}) > 0$). 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:[25]

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

1. *the strong lender makes a profit $\pi_s = \frac{\Delta}{1+\tau}$ and the weak lender makes a zero profit $\pi_w = 0$;*
2. *the strong lender always makes an offer upon seeing a high signal ($m_s = 1$), and its interest rate is randomly drawn from the distribution $\overline{F}_s(r) = \phi(r)$, which has support $[\underline{r}, \overline{r}]$ with $\underline{r} = \frac{1-x_w}{\tau}$ and has a mass point of size $\lambda_s = \phi(\overline{r})$ at $\overline{r}$; and*
3. *the weak lender makes an offer with probability $m_w = 1 - \phi(\overline{r})$ upon seeing a high signal, and when it makes an offer the interest rate is randomly drawn from the distribution*

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

[25] It is worth noting that Proposition 1 applies to the (generic) case of $x_s > x_w$ only; the edge case $x_s = x_w$ is slightly trickier. There are two asymmetric equilibria (which are the continuous limits of the equilibrium in Proposition 1), depending on which lender always makes an offer upon seeing a good signal. There is also a symmetric equilibrium where neither lender always makes an offer upon seeing a good signal (i.e., $m_s = m_w < 1$). 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.

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

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

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

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

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

Corollary 1. *In the competition equilibrium,*

1. *when the screening ability gap* Δ *increases or the average credit quality* τ *decreases, the strong lender's profit (which is also the industry profit) increases; and*

2. *when the strong lender's screening ability* x_s *improves, or the weaker lender's screening ability* x_w *deteriorates, or the average credit quality* τ *decreases, both lenders charge a higher interest rate in the sense of FOSD, and the weak lender makes an offer less frequently conditional on seeing a high signal.*

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

2.4 Borrower Surplus

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

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

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

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

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

It is the high-type's pecuniary payoff from the project and equals $\overline{r}$ net of the expected interest rate in (8).[26]

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

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

where δ is the low-type's non-monetary benefit from getting a loan as we have introduced before for the low-type borrower.

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 due to a higher screening ability of the strong lender (i.e., a higher x_s); high-type borrowers also benefit from a higher screening ability of the weaker lender (i.e., a higher x_w), but low-type borrowers benefit from a higher screening ability of the weaker lender (i.e., a higher x_w) if and only if $\frac{\overline{r}}{\underline{r}} < 1 + \sqrt{x_s}$.*

The first result is straightforward from Corollary 1: A higher average credit quality lessens the winner's curse and so intensifies competition, and it also increases the chance that the weak lender makes an offer upon seeing a good signal. The high-type benefit from both effects and the low-type benefits from the second.

The intuition for the second result is as follows: When x_s is improved, the screening ability gap Δ widens and this softens competition, and at the same time, the weak lender makes an offer less likely as it faces a more severe winner's curse. The high type suffers due to both effects and the low-type suffers due to the second. On the other hand, when x_w is improved, the ability gap Δ shrinks and this intensifies competition, and at the same time the weak lender is more likely to make an offer upon seeing a good signal (but for a low type borrower, the chance of generating a good signal declines). The high type benefits from both effects and the low type can be ambiguously affected by the second effect.

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

In general, a change in screening ability brings about an informational effect, which enhances the screening efficiency; and a strategic pricing effect that affects the equilibrium interest rate as well as the likelihood of a loan offer from the weak lender upon a good signal.[27] 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 *b*ank (denoted by b) and a *f*intech 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. The main message in this section is: under mandatory sign-up, open banking can harm all borrowers compared to the case of no open banking if it overempowers the fintech; voluntary sign-up can mitigate this potential perverse effect, but it is not a full solution, i.e., it is still possible that all borrowers get hurt under open banking with voluntary sign-up. This tends to happen more likely when the average credit quality in the market is relatively low (conditional on lenders are profitable).

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

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

[27] In our setup with $\mu_h = 1$ and $\mu_l = 0$, the first informational effect vanishes for the high-type borrowers since they always generate a good signal, and the interest rate effect in strategic pricing vanishes for the low-type borrowers since they never repay the loan.

It is useful to compare open banking to the common practice of credit reports provided by credit score agencies. First, as mentioned in Section A.1, 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 traditional lenders heavily rely on credit reports on 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 of access to your credit report when you apply for credit,[28] but lenders need to "buy" credit reports from credit agenices. Lenders are therefore costly acquiring information, a mechanism well-studied by existing literature, rather than borrowers are controlling their own data in open banking as emphasized in this paper. This is what is behind UltraFICO mentioned in 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 and so the lenders' prior beliefs of the average credit quality remain unchanged. This is not the practice of open banking regulation, but it is a useful benchmark.

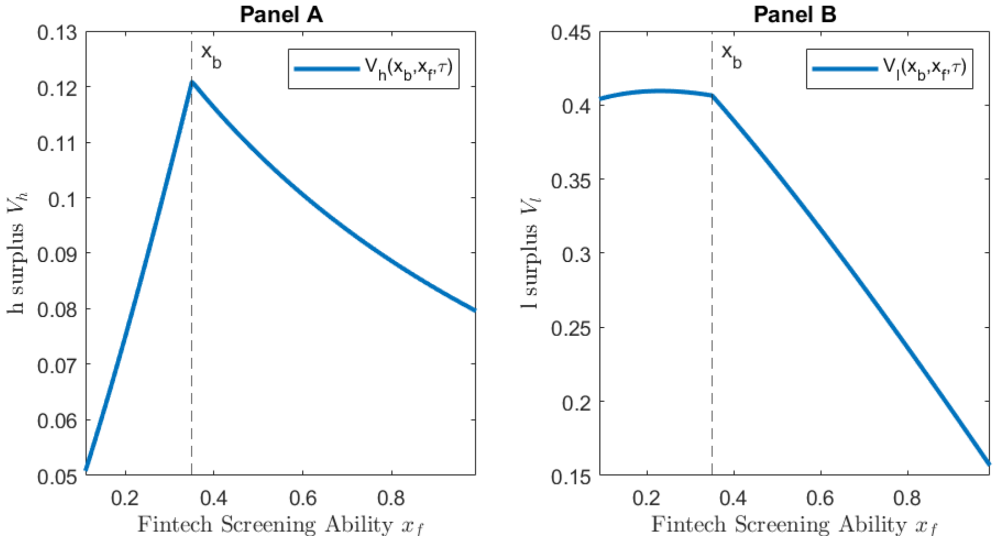
Before open banking, the traditional bank is the strong lender and earns a positive profit $\frac{\Delta}{1+\tau} = \frac{x_b - x_f}{1+\tau}$, and the fintech earns a zero profit; after open banking, the fintech becomes the strong lender and earns a positive profit $\frac{\Delta'}{1+\tau} = \frac{x'_f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

Open banking increases the weak lender's screening ability from x_f to x_b and may expand or shrink the screening ability gap between the two lenders. So its impact on borrowers is less straightforward. Open banking benefits borrowers of type $i \in \{h, l\}$ if and only if $V_i(x_b, x'_f, \tau) > V_i(x_f, x_b, \tau)$. (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 $x_f < x_b$ non-monotonically 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 above x_b after open banking, both types of borrowers suffer from 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

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

Figure 1: Borrower Surpluses when Fintech Screening Ability x_f Varies



High-type borrower surplus (Panel A) and low-type borrower surplus (Panel B). We plot both 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 $\tau = 3.4$.

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 from open banking only if it widens the gap (i.e., if $\Delta' > \Delta$), in which case the low type must suffer from open banking while 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 from open banking, it must be that these low-type borrowers are less likely to get a loan, which improves the market efficiency if there is an efficiency loss associated with them (which is the case as long as the low-type private benefit of receiving a loan $\delta < 1$).

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 below 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 can 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

We now turn to the practically relevant case in which signing up for open banking is voluntary. Consistent with the spirit of GDPR in the EU (i.e., it is the customers, not the bank or the firm more generally, who own their personal data), the recent open banking regulation in various countries gives 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, and if yes, is the underlying mechanism general?

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. We will discuss the implication of $\rho > 0$ on the welfare effect of open banking later sections.

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 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. Our analysis does not depend on the exact interpretation of the sign-up cost.

The purpose of introducing non-tech-savvy borrowers two-fold. First, it captures the reality that some borrowers in practice are averse to open banking and data sharing for some non-economic reasons. Second, by anchoring the updated prior of credit quality in the opt-out market, it enriches the equilibrium outcome as we will explain below.

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 (hence, "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.[29] 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,

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

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

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

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

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 as the weak lender. Note also that the surplus of an i-type non–tech-savvy borrower is $V_i(x_f, x_b, \tau_-)$, since she never signs up for open banking.

A Perfect Bayesian Equilibrium with voluntary sign-up is a collection of

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

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

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

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

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 classify the borrower back into the low-type category.[30]

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 models, 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 first type of pooling equilibrium, if low-type borrowers benefit from open banking when the prior of credit quality remains unchanged, high-type borrowers must benefit as well. It then must be an equilibrium that all tech-savvy borrowers sign up. In the third type of separating equilibrium, the condition implies that low-type borrowers will never sign up: they do not want to

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

even if the credit quality inference becomes the most favorable possible for opting in.[31] 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 $\bar{r}$.

For the second type of semi-separating equilibrium, 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 high types sign up, if all low-type tech-savvy borrowers sign up, then the priors of 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 of 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.[32] 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 (see Section 3.3.3 for a similar point).

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

2. *in the second semi-separating equilibrium, 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 from 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*

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

[32] One 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.

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 between 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 from open banking.

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

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

and

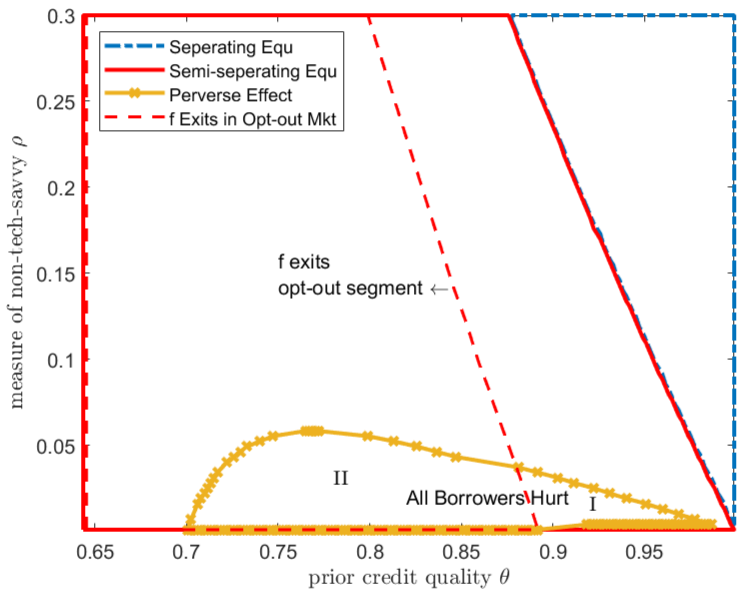
$$V_l(x_f, x_b, \tau_-) = V_l(x_b, x'_f, \tau_+), \tag{15}$$

where $\tau_- = \frac{\rho\tau}{1-(1-\rho)\sigma_l} < \tau < \tau_+ = \frac{\tau}{\sigma_l}$ as we have $\sigma_h = 1$ in the second equilibrium. (These conditions ensure the semi-separating equilibrium, with the second inequality in (14) as the extra condition for high-type tech-savvy borrowers to be worse off.) As both V_h and V_l increase in the prior of 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 from 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 in 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 from 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 those with 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.

Figure 2: Voluntary Sign-up Equilibrium



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

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 from 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 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 size of non–tech-savvy borrowers ρ, while keeping fixed the lender screening technologies that feature a widening gap after open banking.

When the prior average credit quality $\tau = \frac{\theta}{1-\theta}$ is high and more borrowers are non–tech-savvy, opting out does not result in a large deterioration in credit quality inference, so the separating equilibrium arises in which low types opt out, as shown on the upper-right corner with blue dashdotted boundaries in Figure 2. Otherwise, in the lower-left region with red solid boundaries, a semi-separating equilibrium arises and low types are just indifferent between 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, which occurs at the bottom of Figure 2. 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, which 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 where θ is relatively high.

For lower average prior credit quality θ, the endogenous credit quality in the opt-out segment is deteriorating so much that it might even lead to an inactive fintech, as shown in region II in Figure 2. There, only the traditional bank serves in the opt-out segment, and in response 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 from 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 is that the perverse effect of open banking occurs most likely in the market where populations are likely to embrace the open banking technology, and with a relatively low average credit quality (so that the fintech may exit in the opt-out market).

4 Open Banking: Preference Information 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, but a certain type of "precision marketing" based on such information 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 this consideration, and guided by the open-data philosophy mentioned in the introduction, 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 non-credit 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, this preference event is unobservable to both lenders. However, with open banking, this event will be revealed to the fintech lender perfectly among the borrowers who sign up for open banking, so fintech lenders will be able to know exactly when borrowers are "locked in" to fintech loans.

Albeit stark, our modeling of ξ-events is motivated by "event-based marketing," and captures the idea that open banking enables fintech lenders to perform "precision marketing" by combining the newly accessible borrower's banking transaction records with some other existing information (e.g., the borrower's social media data).[33]

Precision marketing in our setting fall into two broad categories. The first is when 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.[34] 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.

The second category is when 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 insurances) unavailable from her bank. 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. 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; a case-by-case decision likely involves a prohibitively high attention cost.[35]

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 that can be potentially identified and targeted by fintech lenders,

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

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

[35]Even if one can swiftly opt out of open banking "without strings attached" as described in the Deloitte Insight survey in the introduction, borrowers are unlikely to know exactly what data will be useful for the fintech, without mentioning that it might be too late to opt out as they have consented to sharing their recent banking history.

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

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

the fintech with a weaker screening ability still makes a zero profit, and the equilibrium structure is similar as in Proposition 1 (i.e., the baseline case of $\xi = 0$). When $\xi > \phi(\overline{r})$, however, both lenders earn a positive profit with a different equilibrium structure. In fact, by simply charging the maximum interest rate $\overline{r}$ (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:

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

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 always makes an offer upon seeing a good signal, while the zero-profit fintech does so with probability $m_f^\xi < 1$. The two lenders' indifference conditions become:

$$p_{HH}\left(\underbrace{(1-\xi)\,\overline{F}_b^\xi(r)}_{\text{win if beats bank}} + \underbrace{\xi}_{\text{win for sure}}\right)\left[\mu_{HH}(r+1)-1\right] - p_{LH} = \underbrace{\pi_f^\xi = 0}_{\text{fintech: zero profit}}, \tag{18}$$

$$\underbrace{(1-\xi)}_{\text{shrunk market size}}\left\{p_{HH}\left(1-m_f^\xi + m_f^\xi \overline{F}_f^\xi(r)\right)\left[\mu_{HH}(r+1)-1\right] - p_{HL}\right\} = \underbrace{\pi_b^\xi > 0}_{\text{bank: positive profit}} \tag{19}$$

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 can be characterized as follows.*

1. *When $\xi < \phi(\overline{r})$, 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 $m_f^\xi = 1 - \phi(\overline{r})$, and the bank's pricing strategy is characterized by $\overline{F}_b^\xi(r) = \frac{\phi(r)-\xi}{1-\xi}$ with $m_b^\xi = 1$. The borrower surpluses are:*

$$V_h^\xi(\tau) = V_h(\tau), \tag{20}$$

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

2. *When $\xi = \phi(\overline{r})$, there exists a continuum of equilibria indexed by $m_f^\xi \in [1-\phi(\overline{r}), 1]$, 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.11.*

3. *When $\xi > \phi(\overline{r})$, 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 $\overline{F}_b^\xi(r) = \frac{\xi}{1-\xi} \cdot \frac{\phi(r)-\phi(\overline{r})}{\phi(\overline{r})}$ and $\overline{F}_f^\xi(r) = \frac{\xi}{\phi(\overline{r})} \cdot \phi(r)$. The borrower surpluses are*

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

$$V_l^\xi = \delta\left[(1-\xi)(1-x_b x_f) + \xi(1-x_f)\right]. \tag{23}$$

The third case of a relatively large $\xi > \phi(\overline{r})$ 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 $\xi < \phi(\overline{r})$ 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 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 non-captured 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.[36]) On the other hand, because the potential

[36] Also, 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.

ξ-event prevents borrowers from taking bank loans, this hurts low-type borrowers who only care about the chance of receiving a loan.[37]

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 who lacks a clearly defined targeted market ($\xi < \phi(\overline{r})$) is struggling with their bottom line while those relatively mature fintech lenders who have established their own niche markets thrive.

Finally, in the knife-edge case (2), when $\xi = \phi(\overline{r})$ there exists a continuum of equilibria indexed by $m_f^\xi \in [1 - \phi(\overline{r}), 1]$, 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, $m_f^\xi = 1 - \phi(\overline{r})$ corresponds to case (1) with $\xi < \phi(\overline{r})$, while $m_f^\xi = 1$ corresponds to case (3) with $\xi > \phi(\overline{r})$. 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.[38] 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 $\overline{r}$ in their ξ-events whenever it sees a good signal. For borrowers in their non–ξ-events, lenders compete as in Proposition 1, leading a zero profit for the fintech.[39] The fintech's expected profit hence is:

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

Superscript "ξ, OB" indicates the ξ-event model under open banking. For borrower surplus, in the ξ-event, a high-type borrower is charged $\overline{r}$ (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

[37] The 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 prob. $1 - x_b$) but the fintech does not make any loan (which occurs with probability $x_f + (1 - x_f)\phi(\overline{r})$, the fintech either receives a bad signal, or a good signal but does not lend). This explains $\xi(1 - x_b)(x_f + (1 - x_f)\phi(\overline{r}))$ in Eq. (21).

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

[39] Note that this does not require the bank to observe whether or not a borrower is in her ξ-event. The bank knows that it has no chance to win a borrower in her ξ-event anyway.

type-dependent borrower surpluses are:

$$V_h^{\xi,OB}(\tau) = (1-\xi) V_h(\tau), \tag{25}$$
$$V_l^{\xi,OB}(\tau) = (1-\xi) V_l(\tau) + \delta\xi(1-x_f), \tag{26}$$

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 $\hat{\xi} \in (\phi(\overline{r}), 1)$ such that high-type borrowers suffer from open banking with mandatory sign-up if and only if $\xi \leq \hat{\xi}$, while low-type borrowers suffer if and only if $\xi > \phi(\overline{r})$. Therefore both types of borrower strictly suffer when $\xi \in \left(\phi(\overline{r}), \hat{\xi}\right)$; 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 $\xi > \phi(\overline{r})$: after open banking, the fintech with a relatively mature business model will compete more aggressively for non--ξ-event borrowers. When $\xi \leq \phi(\overline{r})$, 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 $\xi < \phi(\overline{r})$ so that the underdeveloped fintech still earns zero profit before open banking, the high type suffer from open banking which facilitates the fintech to target their ξ-events. In comparison, 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 relatively mature business model so that $\xi > \phi(\overline{r})$, 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 $\xi \to 1$. Before open banking, knowing that the fintech will be the de facto monopolist, both lenders charge interest rates that converge to $\overline{r}$. 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 from 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:

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

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 $\phi(\overline{r};\tau_-)$—is now endogenous and depends on the updated opt-out prior τ_-. For this reason, we write the dependence of τ_- of $\phi(\overline{r};\tau_-)$ explicitly; $\phi(\overline{r};\tau_-)$ 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 $\xi < \phi(\overline{r};\tau)$, there exists a unique equilibrium where no borrowers sign up, i.e., $\sigma_h = \sigma_l = 0$;*

2. *when $\phi(\overline{r};\tau) < \xi < \phi(\overline{r};\rho\tau)$, 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 $\xi = \phi(\overline{r};\tau_-)$; and*

3. *when $\xi > \phi(\overline{r};\rho\tau)$, 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 $\xi < \phi(\overline{r};\tau)$. 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.

The intuition is as follows. 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 from 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).

This gives rise to 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. Then the low type would not sign up either because doing so would reveal their credit quality type. Consequently, the only equilibrium is nobody signing up.

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 in 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.

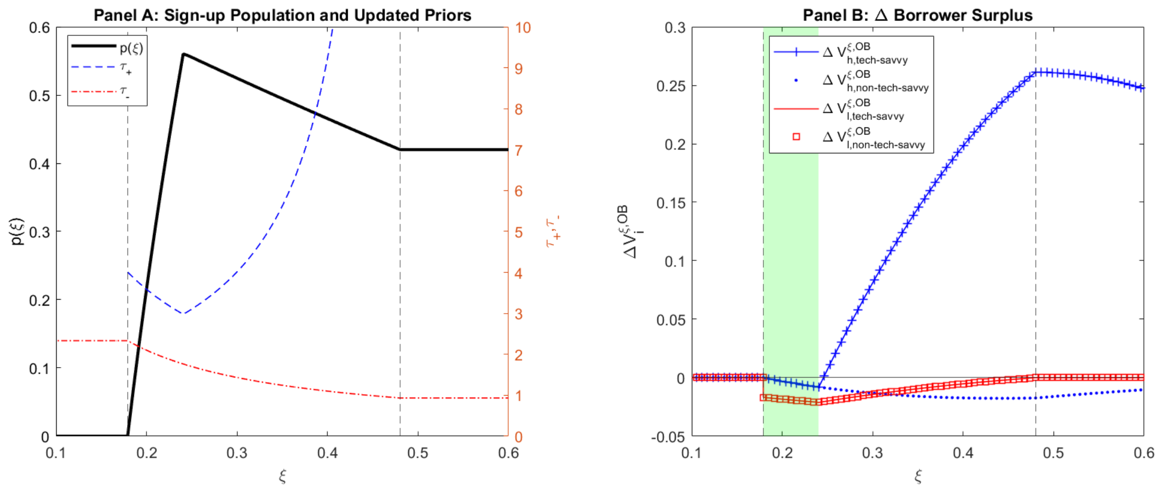
4.4 Impact of Open Banking and Voluntary Sign-up

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

$$p(\xi) \equiv (1-\rho)\left[\theta\sigma_h(\xi) + (1-\theta)\sigma_l(\xi)\right]. \tag{28}$$

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 $\xi \in \left[\phi(\bar{r}; \tau), \tilde{\xi}\right]$, 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 open banking 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_+ increases with ξ and diverges to ∞ as $\xi \to \phi(\bar{r}; \rho\tau)$; 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 non-monotonic relation between the equilibrium sign-up population $p(\xi)$ and ξ. A casual thinking might suggest that $p(\xi)$ decreases with ξ, as ξ captures the borrowers' concern against 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,[40] our analysis on the interaction between consumer preferences and credit quality calls for a more careful examination of this conventional wisdom. In our model, nobody shall sign up for open banking when fintech lenders are still lacking 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 a higher 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,[41] consider $\xi' = \phi(\bar{r};\tau) + \epsilon$ 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 shaded green area even when sign-up is voluntary.

The intuition for high-type borrowers is as follows. For the tech-savvy high-type borrowers who choose to sign up, they suffer from 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 be 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

[40] Since the creation of the Open Banking Implementation Entity (OBIE) by in the U.K. in 2016, the industry has witnessed 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`.

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

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).[42]

5 Conclusion

As the volume of data created by the digital world continues to grow, customer data has evolved into a defining force in every aspect of the banking business. Open banking regulation that requires 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 the data should be open to outside third parties at the consent of customers who generate them.

We offer the first theoretical study on the consequence 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: 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, 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 modern financial industry.

There are a few other important issues on open banking that we leave for future research. First, we have adopted the simplest model structure—two lenders—to study credit market competition. Although it is consistent with search friction in practice (for instance, Allen, Clark, and Houde (2014) show that in Canada borrowers who search for more than a single mortgage quote negotiate with 2.25 financial institutions on average), open banking could substantially enlarge the consideration set of borrowers (Clark, Houde, and Kastl (2020)) by alleviating search frictions and/or expand inclusive financing to borrowers with only online footprints without bank accounts.

Second, traditional banks operate not only in the lending market but also in the deposit and payment service market. Open banking affects their competition with fintech challengers in the

[42] The 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.

latter market 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. Third, from a long-term perspective, should successful fintech giants also be required to share data back with traditional banks? Last but not the least, we take open banking regulation as given; but is it better than the market mechanism where traditional banks act as data brokers and sell their data (upon customer consent) to fintechs?

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A Appendix A

A.1 Open Banking: A Brief Overview

In this brief overview of open banking, we illustrate the underlying API 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 on how banks deal with your financial information, called for by the Competition and Markets Authority (CMA), the competition watchdog in the UK. Together with PSD2, all UK-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 their permissions. Besides other data security measures, the CMA sets up the Open Banking Standard for Application Programming Interfaces (APIs), which are intelligent conduits that allow for secure data sharing among financial institutions in a controlled yet seamless fashion. Via APIs, customers can connect their bank accounts to an app that can analyze their spending, recommend new financial product (e.g., credit cards), or sign up to a provider which displays all of their accounts with multiple banks in one place so they have a better overview of your finances.[43]

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, as well as offering 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

[43]In practice, there are two main ways, screen-scraping and APIs, that third parties can access your 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 U.S. to tranfer 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).

aggregation companies, e.g., Mint, sit in the second segment, in which financial institutions create partnerships with fintechs get access to traditional banks's financial data via APIs, so that consumers can manage their personal finances from a single dashboard.

Taking one step further from "information aggregators," the third segment "lending marketplaces" aim 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. who specialize in invoice financing (see quote):

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

While incumbents still hold the keys to the vault in terms of rich transaction data as well as trusted client relationships, banks often view the opening of these data flows as more threat than opportunity.[44] This is especially true for fintech challengers who are offering 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 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. survived through the pandemic, the OBIE together with Ipsos MORI reported that 50% of surveyed small businesses are now using open banking providers by 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 not a European initiative anymore, as more and more countries are becoming Open Banking friendly.[45] 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 Open Banking ecosystem. For concrete examples, see Ultra FICO and the recent development of REACh in U.S. in Introduction.

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

[45] https://www.finextra.com/blogposting/20219/banking-and-fintech-in-2021-discover-exploding-trends

A.2 Notation Summary

Table 1: Notation Summary

Notation	*Definition and Meaning*	*Characterization*
θ	Probability of high-type	
τ	Likelihood ratio of high-type	$\tau = \frac{\theta}{1-\theta}$
ρ	Proportion of non–tech-savvy borrowers	
$\mu_i,\ i \in \{h, l\}$	Probability that a high/low-type repays	$\mu_h = 1$
$\delta_i,\ i \in \{h, l\}$	Borrower's private benefit of receiving a loan	$\delta_h = 0, \delta_l = \delta > 0$
$V_i(x_w, x_s, \tau)$	Borrower i's surplus	
$j \in \{b, f, s, w\}$	Lender: traditional *b*ank, or *f*intech; *s*trong, or *w*eak	
$S_j \in \{H, L\}$	Signal of lender j, is H or L	
x_j	Screening ability of lender j in "bad news" structure	$\mathbb{P}(S_j = L\|l) = x_j$
$p_{HH}, p_{HL}, p_{LH}, p_{LL}$	Probabilities of lender signals	
$\mu_{HH}, \mu_{HL}, \mu_{LH}, \mu_{LL}$	Probabilities of repayment for borrowers with given signals	
$\overline{r}$	Upper bound of net interest rate (exogenous)	
$\underline{r}$	Lower bound of net interest rate	
m_j	Probability that lender j grants a loan given $S_j = H$	
r_j	Net interest rate offered by lender j	
$F_j(r); \overline{F}_j(r)$	CDF of r_j; survival function of $F_j(r)$	$\overline{F}_j(r) = 1 - F_j(r)$
λ_j	The mass point of $F_j(r)$ at $\overline{r}$	$\lambda_j = \lim_{r \uparrow \overline{r}} \overline{F}_j(r)$
π_j	Lender j's profit	
$\phi(r)$		Eq (6)
Δ	Gap of 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.3 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. $m_s = m_w = 1$). From the two lenders' indifference conditions, we can see that as $r \uparrow \overline{r}$, at least one of $\overline{F}_s(r)$ and $\overline{F}_w(r)$ will be zero since it is impossible that both distributions have a mass point at $r = \overline{r}$. Thus, at least one of the lenders will make a negative profit, which is a contradiction.

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

A.4 Proof of Proposition 1

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

A.5 Proof of Corollary 1

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

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

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

with respect to x_s is proportional to

$$\tau r - (1 - x_w) \geq 0,$$

where the inequality is because $\underline{r} = (1 - x_w)/\tau$. It is easy to see that $\overline{F}_w(r)$ decreases in both x_w (as the numerator decreases in x_w and the denominator increases in x_w) and τ (as the denominator increases in τ). □

A.6 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 make offers more likely 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 make offers less likely 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 offers loans more likely upon seeing a good signal, and so the high-type must become better off. But now the weak lender receives a high signal less likely from 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. □

A.7 Proof of Corollary 2

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

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

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

where

$$\phi(\bar{r}) = \frac{x + \Delta}{\frac{\tau}{1-x}\bar{r} - 1 + x + \Delta}.$$

Its derivative with respect to x equals

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

where the inequality is from $0 < x < 1$ and Assumption 1 which implies $\bar{r}\tau - (1-x) > 0$.

For the low-type borrowers,

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

Its derivative with respect to x equals

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

□

A.8 Proof of Lemma 2

Proof. We prove the result by considering two cases.

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

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

and

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

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

$$x_f' \left[x_b + (1 - x_b)\, \phi_+ (\overline{r})\right] \leq x_b \left[x_f + (1 - x_f)\, \phi_- (\overline{r})\right].$$

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

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

and so

$$\phi_- (\overline{r}) > \phi_+ (\overline{r}). \tag{29}$$

Using the expression for the ϕ function, we have

$$\phi_- (\overline{r}) = \frac{x_b}{\frac{\overline{r}}{\underline{r}_-} - (1 - x_b)} > \phi_+ (\overline{r}) = \frac{x_f'}{\frac{\overline{r}}{\underline{r}_+} - (1 - x_f')} > \frac{x_b}{\frac{\overline{r}}{\underline{r}_+} - (1 - x_b)},$$

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

$$\underline{r}_- > \underline{r}_+. \tag{30}$$

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

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

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 $\tau_+ \geq \tau$ and so both lenders are active in the opt-in market. In the opt-out market, if none of the lenders are active, our result is trivially true; if only one lender is active, it must charge a monopoly interest rate $\overline{r}$, and so the high-type must strictly prefer to sign up, in which case our result is also true. Second, suppose $\sigma_h < \sigma_l$. Then $\tau_- > \tau$ and so both lenders must be active in the opt-out market. If none of the lenders are active in the opt-in market, our result is of course true; if one lender is active in the opt-in market, it must be the fintech with the highest screening ability x_f', and so the low-type must prefer the opt-out market where there are two active lenders with lower screening abilities. □

A.9 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 $V_h(x_b, x'_f, \tau_+) = \overline{r}$, 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 non-trivial equilibria, the tech-savvy high-type borrowers must sign up for open banking for sure, and so $\tau_- \leq \tau_+$.

Characterizing the condition for each type of equilibrium. Notice that it is possible that τ_- becomes sufficiently low so that at least one lender is inactive in the opt-out market. For this reason, we first extend the expression for $V_l(x_f, x_b, \tilde{r})$ as follows:

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

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

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

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

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 actually also a sufficient condition since Lemma 2 implies that the high-type borrowers must want to sign up given the low-type want to. Meanwhile, the above condition also implies $V_l(x_f, x_b, \tau_-) < V_l(x_b, x'_f, \tau_+)$ for any $\sigma_l < 1$ as V_l increases in the average credit quality, and so the other two types of equilibrium cannot be sustained.

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

$$V_l(x_f, x_b, \tau_-(\sigma_l)) = V_l(x_b, x_f', \tau_+(\sigma_l)). \tag{33}$$

This is actually also a sufficient condition since Lemma 2 then 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 actually also a sufficient condition since the condition for the high-type to sign up, i.e., $V_h(x_f, x_b, \rho\tau) \leq V_h(x_b, x_f', \infty) = \bar{r}$, is automatically satisfied in this case. 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.

The details of how to determine $\sigma_l \in (0,1)$ 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 will be inactive in 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 will be active in the opt-out market. $\sigma_l' \in (0,1)$ is well defined if $\rho\tau\bar{r} < 1 - x_f$, $\sigma_l'' \in (0,1)$ is well defined if $\rho\tau\bar{r} < 1 - x_b$, and $\sigma_l'' < \sigma_l'$ in the latter case. More explicitly, we have

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

We need to deal with three cases separately:

(i) $\rho\tau\bar{r} \geq 1 - x_f$. In this case, 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

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

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

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

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

Otherwise, if $V_l(x_f, x_b, \tau_-(\sigma'_l)) \leq V_l(x_b, x'_f, \tau_+(\sigma'_l))$, 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) $\rho\tau\overline{r} \leq 1 - x_b$. In this case, depending on the relationship between the equilibrium σ_l and σ'_l, σ''_l, in the opt-out segment, fintech may exit and bank may randomly pass upon good signal in equilibrium. 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 $\sigma_l \in (\sigma''_l, \sigma'_l)$, fintech becomes inactive in the opt-out segment while 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 bank is active in the opt-out segment but it makes zero profit and randomly drops out upon good signal. □

A.10 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 non-empty set of primitive parameters such that (14) and (15) hold. First, by continuity we can focus on the case of $x_b = x_f$. (Our argument below continues to work when x_b and x_f are sufficiently close to each other.)

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

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

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

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

Finally, we need (15) to hold for some parameters. The remaining parameter we can choose is x'_f. When $\tau_- \overline{r} = 1 - x_f$, one can check that $\frac{V_l(x_f, x_b, \tau_-)}{\delta} = 1 - x_b$. Then (15) requires

$$x_b = x'_f \left(x_b + (1 - x_b) \frac{x'_f}{\frac{\overline{r}\tau_+}{1-x_b} - 1 + x'_f} \right). \tag{36}$$

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

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

$$\frac{n_+}{1 + \tau_+} + \frac{n_-}{1 + \tau_-} = \frac{1}{1 + \tau}. \tag{37}$$

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

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

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

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

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

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

where the inequality used (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 from open banking. (This is because from Corollary 2, we know that V_h increases in the base screening ability and the average credit quality but decreases in the ability gap. In the sign-up market segment, the base ability improves from x_f to x_b and the average credit quality improves from τ and τ_+, and so the high-type borrowers become worse off only if $\Delta' > \Delta$.)

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

A.11 Proof of Proposition 5

Before open banking, fintech cannot condition its strategy on the ξ-event. Similar results as in baseline competition apply here: when making an offer, lenders randomize over common support $\left[\underline{r}^{\xi}, \overline{r}\right]$, and at most one of them can have a mass point at the top $r = \overline{r}$.

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

Proof. From the discussion of ξ's critical value (see Equation 17), if $\xi < \phi(\overline{r})$, fintech's profit in the ξ-event is dominated by the winner's curse in the non--ξ-event when evaluated at $r = \overline{r}$. Hence, by the same argument in Proposition 1, one lender makes zero profit and randomly drops out upon seeing a good signal, and the other lender earns a positive profit, always makes an offer and has a mass point at $r = \overline{r}$, such that both lenders to be willing to offer at $r = \overline{r}$. Similar to the argument in Lemma 1, if $\pi_f^{\xi} > \pi_b^{\xi} = 0$, then $(1-\xi)\,\pi_f^{\xi} > \pi_b^{\xi}$, which further implies $p_{LH} < p_{HL}$, contradiction. Therefore, following Proposition 1, there exists a unique mixed strategy equilibrium with fintech randomly dropping out $m_f^{\xi} < 1$ and traditional bank's mass point λ_b^{ξ} at the top.

The equilibrium characterization largely follows from the baseline model. Recall $\phi(r) = \frac{x_b}{\frac{\tau}{1-x_f}r-(1-x_b)}$ given in (6). Then (18) yields:

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

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

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

The traditional bank's indifference condition (19) is the same as in the baseline, so fintech's strategy must be the same as in the baseline: upon seeing a good signal, it makes an offer with probability $m_f^{\xi} = 1-\phi(\overline{r})$, and the offer randomizes over $\left[\underline{r}^{\xi}, \overline{r}\right]$ according to

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

We now derive the borrower surplus. As the mixed-strategy equilibrium here only differs from the baseline case in $\overline{F}_b^{\xi}(r) = \frac{\phi(r)-\xi}{1-\xi}$ (and $\lambda_b^{\xi} = \frac{\phi(\overline{r})-\xi}{1-\xi}$), it is convenient to illustrate the borrower surplus as the benchmark surplus V_i plus a wedge due to the ξ-event. The high-type borrowers care about the expected interest rate, so

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

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

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

In the $1-\xi$ event, the equilibrium differs from baseline equilibrium only in $\overline{F}_b^{\xi}(r)$, and thus a low type who does not care about pricing has the same surplus $V_l(x_f, x_b, \tau)$ as in baseline; in the ξ-event, the fintech is the only lender, and the borrower only receives the loan when (wrongly) tested with H (probability $1-x_f$) and the fintech does make the offer (probability $m_f^{\xi} = 1-\phi(\overline{r})$). □

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

Proof. When $\xi = \phi(\overline{r})$, from lenders' indifference conditions (18) and (19), we know lender profits π_b^{ξ}, π_f^{ξ}, lowest interest rate $\underline{r}^{\xi}$, and bank pricing distribution $\overline{F}_b^{\xi}(r)$ are the same form as when $\xi < \phi(\overline{r})$. At $r = \overline{r}$, the size of bank's mass point shrinks to $\lambda_b^{\xi} = 0$ exactly, and it follows that the fintech may also yield borrowers to the traditional bank (to make the latter participate) by a mass point at $\overline{r}$, in addition to randomly dropping out upon H as in the case of $\xi < \phi(\overline{r})$. Hence, there exists a continuum of equilibria indexed by $m_f^{\xi} \in [1-\phi(\overline{r}), 1]$ that satisfy $1 - m_f^{\xi} + m_f^{\xi}\lambda_f^{\xi} = \phi(\overline{r})$. Accordingly $\lambda_f^{\xi} = 1 - \frac{1-\phi(\overline{r})}{m_f^{\xi}}$, and $\overline{F}_f^{\xi}(r) = 1 - \frac{1-\phi(r)}{m_f^{\xi}}$ from rescaling (still $1 - m_f^{\xi} + m_f^{\xi}\overline{F}_f^{\xi}(r) = \phi(r)$ as in $\xi < \phi(\overline{r})$). This completes the characterization of the mixed strategy equilibrium.

The choice of m_f^{ξ} affects the probability of receiving the loan and hence low-type's surplus, while high type still earns $V_h^{\xi}(\tau) = V_h(\tau)$. Specifically,

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

□

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

Proof. Similar to Varian (1980), the unique equilibrium is a mixed-strategy one on common support $\left[\underline{r}^{\xi}, \overline{r}\right]$; $\underline{r}^{\xi}$ will be shown to be different from other cases shortly. First, we argue that both lenders have positive profits and always make an offer upon seeing a good signal, so $m_j^{\xi} = 1$ for $j \in \{b, f\}$.

To see this, one feasible strategy for the fintech is to always offer $r = \overline{r}$ upon seeing a good signal, and the associated profit is no less than

$$p_{HH}\xi\left[\mu_{HH}\left(\overline{r}+1\right)-1\right]-p_{LH}=\left(1-\theta\right)x_b\left(1-x_f\right)\left(\underbrace{\frac{\xi}{\phi\left(\overline{r}\right)}}_{>1}-1\right)>0.$$

To make the traditional bank willing to offer at $r = \overline{r}$, fintech has a mass point λ_f^{ξ} at $\overline{r}$ and the traditional bank is open at $\overline{r}$. The traditional bank must also make positive profit $\pi_b^{\xi} > 0$ due to better screening ability.[46]

The fintech's indifference condition is

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

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

$$\pi_f^{\xi} = \xi \cdot \frac{\tau\overline{r}-\left(1-x_f\right)}{1+\tau} - \left(1-\xi\right)\cdot\frac{x_b\left(1-x_f\right)}{1+\tau}, \tag{39}$$

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

$$\underline{r}^{\xi} = \xi\overline{r} + \left(1-\xi\right)\frac{(1-x_b)(1-x_f)}{\tau}. \tag{40}$$

Note that the lower bound here is higher than that in the baseline, $\underline{r}^{\xi} > \underline{r}$, because at lower bound interest rate the fintech serves all borrowers tested with $S_f = H$ in both cases but here $\pi_f^{\xi} > 0$. Lastly, the fintech is indifferent across $r \in \left[\underline{r}^{\xi}, \overline{r}\right)$, implying

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

The bank's indifference condition is

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

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

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

[46] 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 from less serious winner's curse.

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

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

with the mass point $\lambda_f = \xi$. Note that $\overline{F}_f^{\xi}(r)$ strictly increases in ξ, so with a larger ξ the fintech offers loans at higher interest rates in the sense of first order stochastic dominance.

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

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

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

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

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

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

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

A.12 Proof of Proposition 6

Proof. 1. When $\xi \leq \phi(\overline{r})$, 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 fintech's offering probability in the ξ-event. When $\xi > \phi(\overline{r})$, the low type suffer from open banking because by comparing (23) and (26), we have

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

where the inequality holds as $\delta(1-x_b x_f)$ is greater than$V_l(\tau)$ in (10). (The equality will hold if $\tau \to \infty$.)[47] The high type suffer from open banking if

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

which is equivalent to

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

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

2. When $\xi \le \phi(\overline{r})$, 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 $\xi > \phi(\overline{r})$, from (24) and (39) it is immediate to see that the fintech benefits from open banking; while the bank suffers as

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

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

A.13 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 $\left\{m_{j+}^{\xi,OB}, \lambda_{j+}^{\xi,OB}, F_{j+}^{\xi,OB}\right\}$ and $\left\{m_{j-}^{\xi,OB}, \lambda_{j-}^{\xi,OB}, F_{j-}^{\xi,OB}\right\}$ respectively for borrowers who opted in and who opted out.

Contrary to Subsection 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 $\xi < \phi(\overline{r};\tau)$ and the case with $\xi > \phi(\overline{r};\rho\tau)$, 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 $\phi(\overline{r};\tau) \le \xi \le \phi(\overline{r};\rho\tau)$.

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

Proof. First we show that when $\tau_- \le \tau$, low-type has a higher willingness to sign up. The ξ

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

threshold of lender strategy in the opt-out pool is $\phi(\overline{r};\tau_-)$. Note that Condition 27 ensures $\overline{r}\tau_- \geq 1-x_f$. When $\tau_- \leq \tau$, we have $\phi(\overline{r};\tau_-) \geq \phi(\overline{r};\tau) > \xi$, so for the opting out borrowers, lender strategy and borrower surplus follow Case 1 in Proposition 5. Then for high-type to be willing to sign up,

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

Hence$V_h(\tau_-) < V_h(\tau_+)$ and $\tau_- < \tau_+$. With the better inference and the effects of ξ-event on low type shown in (21) and (26), 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 low-type has higher willingness to sign up. If $1 > \sigma_h > 0$, then 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 high type's sign up incentive.

We now rule out that a larger proportion of low-type signing up in equilibrium, i.e., $\sigma_l > \sigma_h > 0$ and hence $\tau_- > \tau > \tau_+$. In this case, the endogenous ξ threshold $\phi(\overline{r};\tau_-) < \phi(\overline{r};\tau)$ and lender competition in the opt-out pool may not always follow one case in Proposition 5. If $\xi < \phi(\overline{r};\tau_-)$, the competition follows Case 1 in Proposition 5, but $\tau_- > \tau > \tau_+$ violates high-type's sign up incentive. If $\xi = \phi(\overline{r};\tau_-)$ we show later that it must be $\sigma_l < \sigma_h$; and if $\phi(\overline{r};\tau_-) < \xi < \phi(\overline{r};\tau)$, we show later that $\sigma_h = 1, \sigma_l = 0$. The last two cases have $\sigma_l < \sigma_h$ hence contradict with the premise that "larger proportion of low-type signing up in equilibrium."

Hence the only possible equilibria is $\sigma_h = \sigma_l = 0$ and $\tau_- = \tau_+ = \tau$, under which lender strategy is Case 1 in Proposition 5. Introduce $\hat{\tau}$ as the threshold τ_+ for 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 satisfy $\tau_+ < \hat{\tau}$, high-type borrower does not sign up, and low-type also does not want to sign up to be revealed.

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

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

Proof. Note that $\tau_- = \rho\tau$ is the lower bound of τ_-, and is reached when all tech savvy high-type sign up,$\sigma_h = 1$, but none of the low-type signs up, $\sigma_l = 0$. Hence, for any possible equilibrium belief τ_-, we have $\xi > \phi(\overline{r};\rho\tau) \geq \phi(\overline{r};\tau_-)$: lender competition for borrowers who did not sign up always follows Case 3 in Proposition 5.

Eq. (42) says it is a dominant strategy for the l-type borrower not to sign up, $\sigma_l = 0$. Then if anyone were to sign up, it must be a high-type borrower and $\tau_+ = \infty$. As a result, in the non–ξ-event, lenders compete for the opt-in segment a 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, $(1-\xi)\,\mathbb{E}\left[\min\left\{r_b^{\xi}, r_f^{\xi}\right\}\right] + \xi\mathbb{E}\left[r_f^{\xi}\right]$:

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

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 signs up and $\tau_- = \tau$, which contradicts with $\phi(\bar{r};\tau) \le \xi$; if $\xi > \phi(\bar{r};\tau_-)$, only tech-savvy high-type borrowers opt in and $\tau_- = \rho\tau$ which contradicts with $\xi \le \phi_-(\bar{r};\tau_- = \rho\tau)$. Hence, when $\phi(\bar{r};\tau) \le \xi \le \phi(\bar{r};\rho\tau)$, in equilibrium ξ is on the cutoff $\xi = \phi(\bar{r};\tau_-)$.

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

1. Say $\sigma_l = 0$. If $\sigma_h = 0$, then $\tau_- = \tau_+ = \tau$ and $\xi > \phi(\bar{r};\tau_-)$, lenders compete for the opt-out segment following Case 3 in Proposition 5, which leads to $\sigma_h = 1$, $\sigma_l = 0$, 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, 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 $\tau_- \ge \tau$ and $\xi > \phi(\bar{r};\tau) \ge \phi(\bar{r};\tau_-)$. Lender competition in the opt-out segment leads to sign-up strategies $\sigma_h = 1$, $\sigma_l = 0$, contradiction.

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

$$\tau_- = \frac{1-x_f}{\bar{r}}\left(\frac{x_b}{\xi} + 1 - x_b\right). \tag{43}$$

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 high-types either indifferent or strictly prefer to sign up (i.e., $\sigma_h > 0$). Specifically, borrower surplus for not signing up are

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

where $m_{f-}^{\xi,OB}$ versus mass point at $r=\overline{r}$ 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 $m_{f-}^{\xi,OB}\geq 1-\phi(\overline{r};\tau_-)$ make both type of borrowers indifferent:[48] $V_{i,-}^{\xi,OB}(\tau_-)=V_{i,+}^{\xi,OB}(\tau_+)\,,\ i=h,l$. Hence, we have[49]

$$\phi_+(\overline{r})=\frac{2x_b+(1+\xi)(1-x_b)-\sqrt{[2x_b+(1+\xi)(1-x_b)]^2-4\xi(x_b+(1-x_b)\xi)}}{2(x_b+(1-x_b)\xi)},\qquad(45)$$

and

$$m_{f-}^{\xi,OB}=1-\frac{(1-\xi)x_b\phi_+(\overline{r})}{\xi+(1-\xi)x_b}.\qquad(46)$$

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

$$\sigma_h=\frac{\frac{\tau_+}{\tau_-}-\frac{\tau_+}{\tau}}{(1-\rho)\left(\frac{\tau_+}{\tau_-}-1\right)}\text{ and }\sigma_l=\frac{\frac{\tau}{\tau_-}-1}{(1-\rho)\left(\frac{\tau_+}{\tau_-}-1\right)},\qquad(47)$$

where τ_- is determined in (43) and τ_+ is determined by (45) and (6). Note that $\frac{\partial}{\partial\tau_-}\phi(\overline{r};\tau_-)<0$ implies that $\tau_-<\tau<\tau_+$ for $\xi>\phi(\overline{r};\tau)$ and $\phi(\overline{r};\tau_-)=\xi$. As a result, $\sigma_h>\sigma_l$ from belief updating rule $\tau_+=\tau\frac{\sigma_h}{\sigma_l}$. This observation completes the earlier proof of a unique sign-up equilibrium under " **Small ξ Case**" (i.e., $\xi<\phi(\overline{r};\tau)$) where we rule out $\tau_+>\tau>\tau_-$ with $\sigma_l>\sigma_h$.

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

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

and $m_{f-}^{\xi,OB}$ is determined in (46). Note that this corner equilibrium must arise when $\xi\to$

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

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

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

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

$$(x_b+(1-x_b)\xi)\phi_+^2-[2x_b+(1+\xi)(1-x_b)]\phi_++\xi=0.\qquad(44)$$

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

$\phi(\overline{r};\rho\tau)$; in this situation, we have $\tau_- \to \rho\tau$ and $\tau_+ \to +\infty$, under which

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

and the high-type borrowers strictly prefer to sign up. At the same time, $\sigma_l \to 0$ while low-type borrowers stay indifferent whether or not to sign up.

□

A.14 Proof of Proposition 8

Proof. First we argue that there exists a $\tilde{\xi} \in (\phi(\overline{r};\tau), \phi(\overline{r};\rho\tau))$ such that $0 \le \sigma_h < 1$ when $\phi(\overline{r};\tau) \le \xi < \tilde{\xi}$ and $\sigma_h = 1$ when $\tilde{\xi} \le \xi \le \phi(\overline{r};\rho\tau)$. To see this, we already argued in Appendix A.13 that $\sigma_h = 1, 0 < \sigma_l < 1$ must arise when ξ is sufficiently close to $\phi(\overline{r};\rho\tau)$. When $\xi = \phi(\overline{r};\tau)$, we have $\tau_- = \tau$ and $\sigma_h = \sigma_l = 0$. Hence by continuity of σ_h, σ_l in ξ, there exists such a $\tilde{\xi}$ below which high-type is indifferent to sign up and above which high-type strictly prefers to sign up.

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_-. When $\phi(\overline{r};\tau) \le \xi < \tilde{\xi}$, high-type is indifferent to sign up, so τ_+ must decrease with ξ to balance the deterioration of τ_-. Hence, $p(\xi)$ increases in ξ in this case. On the other hand, when $\xi \ge \tilde{\xi}$, we have $\sigma_h = 1$ and $\sigma_l = \frac{1-\frac{\tau}{\tau_-}\rho}{1-\rho}$, so $p(\xi) \equiv (1-\rho)[\theta + (1-\theta)\sigma_l]$ decreases in ξ.

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

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

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

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

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

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

while their profits before open banking are

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

We hence have that

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

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

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

From (47), we have $(1-\rho)\sigma_l = \frac{\tau-\tau_-}{\tau_+-\tau_-}$, and hence the

$$1 - \frac{\phi(\overline{r};\tau_-)}{\phi(\overline{r};\tau)} + (1-\rho)\sigma_l = \underbrace{\frac{(\tau-\tau_-)}{(\tau_+-\tau_-)(\overline{r}\tau_- - (1-x_b)(1-x_f))}}_{\text{positive}} (2\overline{r}\tau_- - \overline{r}\tau_+ - (1-x_b)(1-x_f)) \tag{48}$$

Hence it boils down to the sign of the last bracket in Eq. (48). Notice that while $\tau_- = \tau$ is continuous at $\xi = \phi(\overline{r};\tau)$, $\tau_+ = \tau\frac{\sigma_h}{\sigma_l}$ typically jumps upward at $\xi = \phi(\overline{r};\tau)$ from left. So it is non-trivial to show that the total financial sector gains even when in the neighborhood of $\xi = \phi(\overline{r};\tau)$.

We use the high-type's indifference curve, which says

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

We then try to ensure that $\tau_+ < 2\tau_- - \frac{(1-x_b)(1-x_f)}{\overline{r}}$ (so that the last bracket in Eq. (48) is positive), by checking the sign of $Q\left(\tau_+ = 2\tau_- - \frac{(1-x_b)(1-x_f)}{\overline{r}}\right)$, which equals

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

Because $Q(\cdot)$ is quadratic and open-upward, and we take the larger solution (see footnote 49), to ensure $Q\left(\tau_+ = 2\tau_- - \frac{(1-x_b)(1-x_f)}{\overline{r}}\right) > 0$ we need

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

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

1. When $\xi = \phi(\overline{r};\tau)$, $\tau_-(\xi) = \tau$, so we require that (recall $\rho\overline{r}\tau \geq 1 - x_f$ in (27))

$$
\frac{2}{\rho}(1-x_b) - (5-x_b)(1-x_b) + 1 > 0. \tag{49}
$$

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

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

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

$$
2(1-x_b)\frac{\tau_+\left(\tilde{\xi}\right)}{\tau_+\left(\tilde{\xi}\right) - (1-\rho)\tau} - (5-x_b)(1-x_b) + 1 > 0, \tag{50}
$$

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

In sum, the simple conditions (49) and (50) guarantee that the financial sector gains after open banking when $\xi \in \left[\phi(\overline{r};\tau), \tilde{\xi}\right]$ (note, these conditions are also necessary if $\rho\overline{r}\tau = 1 - x_f$ and for sufficiently large x_j's). □