OPEN BANKING: CREDIT MARKET COMPETITION
WHEN BORROWERS OWN THE DATA

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

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Abstract

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

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

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

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1   Introduction

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

Open banking, an initiative launched by several governments including the European Union and the United Kingdom, leads such a shift toward the open-data economy. Importantly, the core principle of open banking does not stop at "customer ownership" of their own data. Aiming at "customer control," the Second Payment Services Directive (PSD2) envisions enabling customers to voluntarily share their financial data with other entities via application programming interfaces (APIs). Indeed, PSD2, by mandating European banks embrace the API technology, explicitly empowers customers to share their banking data, removing the financial institution's role as gatekeeper.[1] In the United States where the regulators have taken a much more laissez-faire approach, large players including banks and credit agencies are developing innovative open banking products for their customers. For instance, FICO, Experian, and Finicity jointly launched a pilot program in 2019 called "UltraFICO," through which borrowers can *choose* to share their banking information with lenders, in addition to their traditional FICO scores which generally reflect only a person's borrowing history.[2] 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, to represent a transformative trend in the banking industry over the coming decade.[3]

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[1]More specifically, the PSD2 requires European banks to grant qualified third parties automated access to customer *transaction* accounts, covering both retail and corporate customers, via the API technology. Loosely speaking, 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 discussion on APIs, see Appendix B.

[2]Traditional banks use credit reports as the main tools to determine who gets a loan, leaving customers with only cash or debit cards unserved; we provide more discussion in Section 2.3. In fact, to promote financial inclusion for borrowers with "thin" credit files, 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; see https://bit.ly/3Gj3e9W.

[3]Deloitte Insight conducted a survey on open banking in April 2019, with the following descriptive definition of open banking: "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,

Borrowers' information sharing—especially their bank account data—is instrumental for fintech firms who specialize in small business and consumer lending (say, LendingClub in the U.S. or MarketPlace in the U.K.). Dan Kettle at Pheabs argues that

> Open banking is ... 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 ... But with open banking, we now see the exact bank transactions that customers have had ... In particular, if there is a history of repeat gambling or taking out other high cost loans ... (then) we should be more cautious with this kind of client—maybe declining them or charging a higher rate."

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

Our model in Section 2, following Broecker (1990) and Hauswald and Marquez (2003), considers a traditional bank and a fintech lender who conduct independent creditworthiness tests before making loan offers to borrowers. Each borrower is of either high or low credit quality, and the test yields a noisy signal of their credit quality. Similar to common-value auctions, an important feature of this market is a winner's curse (i.e., winning a borrower implies the possibility that the rival lender has observed an unfavorable signal of the borrower). As shown in Section 3, in equilibrium the lender with a stronger screening ability faces a less severe winner's curse and earns a positive profit, while the other weaker lender earns a zero profit (on average) and sometimes declines to extend an offer even upon seeing a favorable signal.

We use this baseline credit market competition framework to study the impact of open banking in Section 4. Traditional banks enjoy a great advantage from the vast amount of

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

customer data they possess (from transaction accounts, direct deposit activities, etc). Fintech lenders often possess limited data (usually restricted to borrowers' online footprints such as social media activities); however, they are equipped with more advanced data analysis algorithms, though without enough data a better algorithm does not yield more useful information. Therefore, in our benchmark case with no open banking, we assume that the bank has a better screening ability than the fintech lender. (We define screening ability as the joint outcome of data availability and data analysis techniques.)

Open banking, by allowing borrowers to share their banking data, can greatly enhance the competitiveness of the fintech lender as a "challenger." Once the fintech has access to a borrower's banking data, we assume that its screening ability is improved. Since the fintech has a more advanced data analysis algorithm, it can even surpass the bank in screening borrowers, especially when it also has some independent data sources.[4] This improvement of the fintech's screening ability has two effects: a standard "information effect" that helps high credit quality borrowers but hurts low credit quality borrowers, and a "strategic effect" that affects the degree of lending competition. This "strategic effect" can go in either direction: lending competition will be intensified (softened) if the screening ability gap between the two lenders shrinks (expands). In particular, if open banking expands the screening ability gap sufficiently (i.e., if open banking "over-empowers" the fintech), it will hurt both types of borrowers but improve industry profit. Reflecting on the celebrated selling point that open banking aims to promote competition and benefit borrowers, we hence highlight that data sharing may backfire by increasing the competitiveness of the challenger lender too much.

But can the very nature of open banking—borrowers deciding whether to opt in to share their banking data—prevent this perverse effect of open banking on borrowers? After all, borrowers ought not to act against their own interest. We then study open banking with voluntary sign-up decisions, where some borrowers, however, are privacy conscious and never sign up for open banking regardless of their credit quality. We show that when the fintech becomes sufficiently stronger than the bank under data sharing, in the unique nontrivial equilibrium, high-quality borrowers who are not privacy conscious opt in while some low-quality borrowers opt out, and all borrowers are strictly worse off than before open banking. Those who sign up suffer due to weakened competition as a result of the enlarged lender asymmetry, while those who do not sign up suffer due to an adverse equilibrium inference

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[4]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 significantly improve the predictive power of traditional credit bureau data when combined with the latter.

that opting-out signals poor credit quality.[5] We also show that, in any nontrivial equilibrium, privacy-conscious borrowers who never sign up for open banking always get (weakly) worse off, reflecting a negative externality from non-privacy-conscious borrowers who voluntarily choose to share data.

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

In Section 5 we discuss several extensions and check the robustness of our main insight. We first argue that borrowers' affinity for fintech loans (i.e., the possibility that some borrowers strongly prefer fintech lenders) tends to make the perverse effect of open banking more likely to occur: by granting the fintech lender some local market power, fintech affinity complements the fintech lender's screening ability boosted by open banking and so further weakens the lending competition. We also show that the perverse effect can arise if data sharing via open banking reveals information on borrowers' affinity toward the fintech lender (instead of information on credit quality). Overall, these two extensions help illustrate the generality of the perverse effect given the endogenous credit quality inference. However, we also point out that if there is more than one fintech lender, the perverse effect will disappear if they are sufficiently symmetric to each other in their screening ability (both before and after open banking), but will persist if they are sufficiently asymmetric to each other (e.g., when one fintech is a giant tech company and the other is a small startup). Finally, we also discuss a laissez-faire approach to open banking in which banks are allowed to sell their customer data to fintechs; there, we argue that when the bank is willing to sell its data, the

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[5]The adverse inference from not signing up for open banking is similar to the usual unraveling argument in the context of adverse selection (e.g., Milgrom, 1981). In particular, Lizzeri (1999) shows a related perverse effect from the existence of an information intermediary. In his model, if an agent does not buy a certificate from the intermediary, she will be regarded as a low type, and as a result the intermediary is able to extract all the surplus, which makes all agents worse off compared to the case when the intermediary is absent. This channel of surplus extraction, however, does not exist in our model with competing lenders. Our perverse effect also needs the component that an enlarged screening ability gap between lenders softens their competition.

perverse effect of data sharing is most likely to occur.

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

Related Literature

Lending market competition with asymmetric information. Our paper is built on Broecker (1990), who studies lending market competition with screening tests. In Broecker (1990), lenders are *symmetric* and possess the same screening ability, while both our paper and Hauswald and Marquez (2003) consider asymmetric lenders with different screening abilities.[6] Hauswald and Marquez (2003) study the competition between an inside bank that can conduct credit screenings and an outside bank that has no access to screening. They consider the possibility of information spillover to the outside bank, which reduces the inside bank's information advantage and benefits borrowers. Besides that the weaker lender can surpass the stronger one in screening after open banking, our paper also differs from Hauswald and Marquez (2003) in one key aspect: in our context, borrowers can control the information flow between the competing lenders by choosing whether to share their banking transaction data. This sharing decision itself can potentially reveal further creditworthiness information, which is an important source for the perverse effect of open banking to arise.

Asymmetric credit market competition can also arise from the bank-customer relationship, as a bank knows its existing customers better than a new competitor does; this idea was explored by Sharpe (1990).[7] In our model, information asymmetry before open banking exists for the same reason: traditional banks own the customer data that fintech lenders

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

[7]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 induce lenders to acquire less information and so hurt consumer welfare in subprime credit markets, in a similar vein to the perverse effect of open banking in our paper. The lenders' endogenous information acquisition plays a key role in their paper, while our study focuses on the equilibrium inference of borrowers' decisions to share their own data.

cannot access, so that even if fintech lenders have a better data processing algorithm, they screen borrowers less accurately.

Our paper is also related to the literature on credit information sharing among banks—e.g., Pagano and Jappelli (1993) and Bouckaert and Degryse (2006).[8] More broadly, lending market competition with asymmetric information is important for studying many issues such as capital requirements (e.g., Thakor, 1996), borrowers' incentives to improve project quality (e.g., Rajan, 1992), information dispersion and relationship building (e.g., Marquez, 2002) and credit allocation (e.g., Dell'Ariccia and Marquez, 2004, 2006).

Fintechs. Our paper connects to the growing literature on fintech disruption (see, for instance, Vives, 2019; Berg, Fuster, and Puri, 2021, for reviews of digital disruption in banking), in particular on fintech companies competing with traditional banks in originating loans (for empirical evidence, see, Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Tang, 2019; Gopal and Schnabl, 2020).[9] Berg, Burg, Gombović, and Puri (2020) find that even simple digital footprints are informative for predicting consumer default, as a complementary source of information to traditional credit bureau scores.[10]

On the theoretical front, closely related to our work, Parlour, Rajan, and Zhu (2021) study fintechs who specialize in payment services and compete with a monopolistic bank that operates in both payment service and credit (loan) markets. They stress that customers' payment services provide information about their credit qualities, and therefore the fintech competition in payment services disrupts this natural information spillover within

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[8]These two papers differ from ours in terms of focus as well as framework. Pagano and Jappelli (1993) study a collective decision about 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 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.

[9]Blockchain and its underlying distributed ledger technology are another important disruption force in today's financial industry that have received great attention since the launch of Bitcoin. For related work on this topic, see Biais, Bisière, Bouvard, and Casamatta (2019); Cong and He (2019) and Abadi and Brunnermeier (2020).

[10]Di Maggio and Yao (2020) show that 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 fintech affinity studied in Section 5.2. These empirical patterns suggest that fintech lenders rely more on alternative data and have a distinct enforcement method (in contrast to traditional banking which mainly conducts collateral-based lending.) This motives Huang (2022) to investigate lender competition when fintechs and traditional banks have different lending technologies.

the traditional bank. In contrast, our model highlights lender competition, especially when the borrower's transactions information can improve the two lenders' screening technologies differently (due to their different data analysis algorithms). In a recent paper, Goldstein, Huang, and Yang (2022) evaluate the open banking policy by incorporating the endogenous responses from bank's deposit funding (liability side) to bank's loan making (asset side).

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.[11] Aridor, Che, and Salz (2020) offer evidence about the equilibrium "inference" on customers: allowing privacy-conscious consumers to opt out of data sharing under GDPR increases the average value of the remaining consumers to advertisers.

2 The Model

This section introduces the main model of credit market competition and open banking. For convenience, Table 1 in Appendix A.1 lists the notation used in this paper. We summarize our model by the schematic diagram provided in Figure 1.

2.1 Borrowers

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

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

be the likelihood ratio of high-type over low-type borrowers in the population, which represents the average credit quality of borrowers (as reflected by all public information available to lenders, for instance, their credit scores).

We assume that the interest rate in the market never exceeds $\bar{r}$. There are at least two

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

interpretations of this assumption. Borrowers can be small business firms, each having a project in which to invest but differing in the probability that their project will succeed. When the project succeeds, it yields a net return $\bar{r}$, which is observable and contractible; when it fails, it yields nothing. Protected by limited liability, borrowers will never pay an interest rate above $\bar{r}$. Alternatively, borrowers can be ordinary consumers who need a loan to purchase a product but differ in the probability that they will be able to repay the loan. (For instance, a consumer will default if she becomes unemployed, and consumers face different unemployment risks.) In this case, the interest rate is capped at $\bar{r}$ either due to interest rate regulation (e.g., usury laws cap the interest rate in many jurisdictions),[12] or because of some exogenous outside options. We assume that the utility from consuming the product is sufficiently high that borrowers are willing to borrow at $\bar{r}$.[13]

2.2 Lenders and Screening Ability

There are two risk-neutral competing lenders in the market: a traditional bank (denoted by b) and a fintech lender (denoted by f). (We discuss the case with more than one fintech lender in Section 5.3.) When a borrower applies for a loan, each lender conducts a creditworthiness test before deciding whether to make an offer. Following Broecker (1990), we assume that the test is costless and it yields an independent and private signal of a borrower's type.[14] Let $S_j \in \{H, L\}$ denote the signal received by lender j, where $j \in \{b, f\}$. For simplicity, we assume that when a borrower is of high type, each lender is certain to observe a high signal H; when a borrower is of low type, the signal is noisy:

$$\mathbb{P}\left(S_j = L \,|\, l\right) = x_j,$$

where x_j indicates lender j's screening ability. Notice that we adopt a "bad-news" signal structure, i.e., a bad/low signal perfectly reveals a borrower to be of low type, while a

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[12]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.

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

[14]Di Maggio, Ratnadiwakara, and Carmichael (2021) show that Upstart (a fintech lender) and the regulatory model of banks generate different screening outcomes—driven by both the fintech's algorithm and its alternative data.
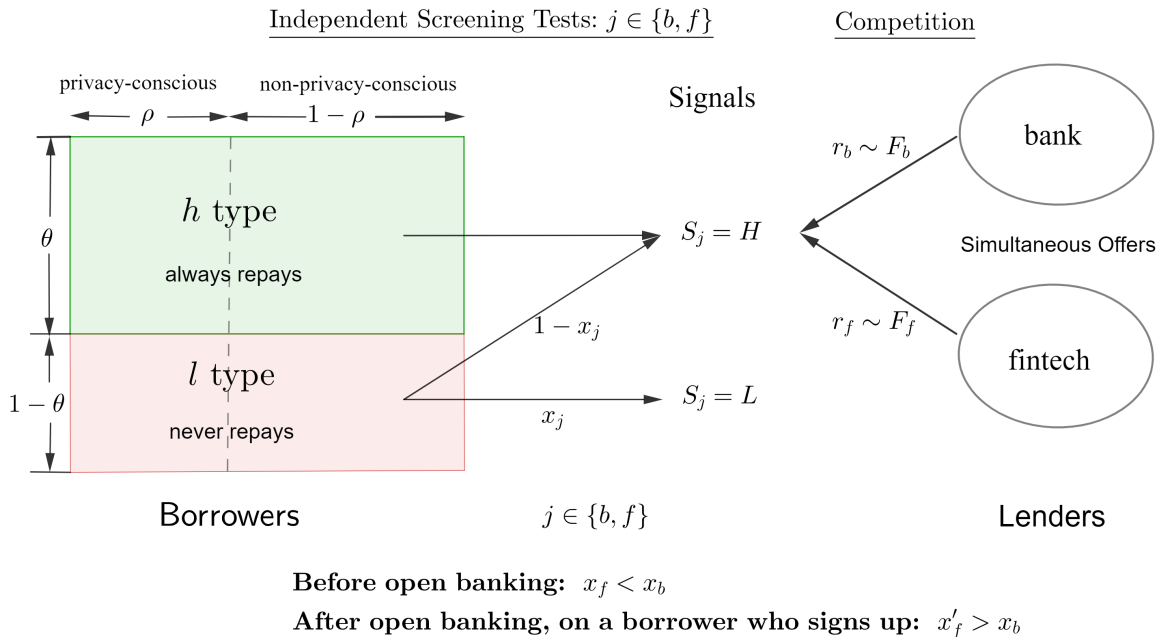
privacy-conscious   non-privacy-conscious

$\overset{\rho}{\longleftrightarrow}$ $\overset{1-\rho}{\longleftrightarrow}$

Signals

$r_b \sim F_b$ bank

h type

always repays $S_j = H$

Simultaneous Offers

$1 - x_j$

θ

$1 - \theta$

l type

never repays $S_j = L$

x_j

$r_f \sim F_f$ fintech

Borrowers $j \in \{b, f\}$ Lenders

Before open banking: $x_f < x_b$

After open banking, on a borrower who signs up: $x'_f > x_b$

Figure 1: Model Scheme.

good/high signal is inconclusive.[15] The two lenders' screening abilities x_b and x_f are assumed to be publicly known. We will specify which lender has a higher screening ability in the next subsection.

After receiving their private signals, lenders update their beliefs about the borrower's type and make their loan offers $r_j \in [0, \bar{r}]$ (if any) simultaneously, aiming to maximize their own profit. The borrower chooses the offer with a lower interest rate.[16] For simplicity, we assume that the two lenders have the same funding costs, which we normalize to 1.[17]

In our setting, no lender will make loan offers to a borrower upon seeing a low signal.

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[15]The main insight of this paper does not rely on this bad-news signal structure, but this simplification greatly helps with tractability and transparency when lenders have asymmetric screening abilities. (See other recent papers such as Hau, Huang, Shan, and Sheng (2019) and Chu and Wei (2021) for different signal structures.) This simple signal structure is also consistent with the empirical pattern of fintechs promoting financial inclusion by serving subprime borrowers: these underserved subprime borrowers have a lower average quality as characterized by a low τ, and fintechs with a relatively high screening ability x_f can screen in and hence serve some high-type borrowers (independent of the bank's screening).

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

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

Upon seeing a high signal, however, lender j is willing to lend at the highest possible interest rate $\bar{r}$ if and only if

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

To see this, 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 $\tau = \frac{\theta}{1-\theta}$ is the prior credit quality. Therefore, lender j is willing to lend at $r = \bar{r}$ if this expected repayment rate times $1+\bar{r}$ exceeds the cost 1, which requires (1). Intuitively, (1) holds more easily when there are more high-type borrowers in the population (i.e., when τ is higher), or when the screening ability is better.

Finally, we assume that any borrower of type i obtains a nonmonetary benefit δ_i just from getting a loan. Since δ_h plays no role in our subsequent analyses, we normalize it to 0 for convenience. We, however, set $\delta_l = \delta > 0$, which can be interpreted as the control rent of entrepreneurs from nonpledgeable income (see, for instance, Tirole, 2010) in the context of small business loans, or consumption utility in the context of consumer loans. This implies that low-type borrowers (who never succeed in the context of small business firms) still care about the likelihood of getting a loan, which renders a meaningful analysis of the low-type borrowers' welfare. For our applications we regard δ as relatively small,[18] though this assumption plays little role as our welfare analysis focuses on the Pareto criterion for consumers without transfer.

2.3 Open Banking and Voluntary Sign-Up

The main innovation in our model is to introduce open banking with voluntary sign-up decisions by borrowers. (We provide a brief overview of open banking in Appendix B.)

Before open banking, we assume that the bank is better at screening borrowers (i.e., $x_b > x_f$) because of its rich data from existing bank-customer relationships via its traditional IT investment (He, Jiang, Xu, and Yin, 2021). After open banking, if the fintech has access to a borrower's data from the bank, we assume that its screening ability for that borrower improves significantly to x_f' so that it exceeds the traditional bank's ability x_b (i.e., $x_b < x_f'$).

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

This is because, for example, the fintech is often equipped with more advanced technology to make use of the data, and it may also have some additional customer information (e.g., from social media) that complements the bank data. In sum, throughout the paper we assume that

$$x_f < x_b < x'_f, \tag{2}$$

which reflects, as emphasized in the introduction, the fact that screening ability is determined by both data availability and the data processing technique/algorithm.

Whether the fintech has access to a borrower's banking data is the borrower's choice. Consistent with the recent development of open banking regulations in various countries, we assume that each borrower has the right to decide whether to sign up for open banking, and a borrower's sign-up decision is observable to both lenders.[19] Since borrowers know their own credit quality type, their sign-up decisions potentially signal their type. This channel of credit quality inference from borrowers' sign-up decisions will play an important role in studying the welfare impact of open banking. In particular, due to this inference channel and its influence on the lenders' pricing strategies, it is ex ante unclear whether the design of voluntary sign-up is a silver bullet for consumer protection.

Signing up for open banking can also involve a direct cost for borrowers: they may be privacy conscious and worry deeply about the security of sharing their own data, and they may also need to learn how open banking works. This sign-up cost should be also heterogeneous across borrowers. To capture this heterogeneity in a simple way, we assume that a fraction $\rho \in (0,1)$ of borrowers, whom we call "privacy-conscious," face a very high sign-up cost so that they never sign up; while the remaining $1 - \rho$ of borrowers, whom we call "non-privacy-conscious," have a zero sign-up cost, and their endogenous sign-up decisions will be our focus.[20] The sign-up cost is also borrowers' private information, and for model parsimony, we assume it is independent of their credit quality type. As we will see, introducing this heterogeneity of privacy-consciousness will also help anchor the updated belief of credit quality among borrowers who opt out of open banking, which sharpens our equilibrium analysis.

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

[20]Alternatively, we can also regard borrowers with a zero sign-up cost as those who are technology savvy and are willing to "encompass" the utilization of modern information technology.

Discussion: Banking data vs credit score. Some readers may wonder whether the information from banking data is the same as that from credit scores. Here we argue that these two types of information can be quite different. First, as mentioned in introduction, credit scores or credit histories do not reflect bank account transaction information, the major data category currently locked inside incumbent banks and targeted by open banking. Given that traditional lenders heavily rely on credit reports for their loan-making businesses, the information from credit scores can be treated as public information among lenders and it determines the prior of a borrower's credit quality measured by τ in our model. In this sense, the market in our model should be regarded as a segment of borrowers who have similar credit scores.

Second, perhaps more importantly, according to Fair Credit Reporting Act (FCRA) borrowers give lenders their consent to access to their credit reports when they apply for credit,[21] but lenders need to "buy" credit reports from credit agencies. This case, therefore, falls under the well-studied mechanism of lenders' costly information acquisition, rather than the case in which borrowers control their own data. This comparison also applies to UltraFICO mentioned in the introduction: any lender can pull a borrower's FICO score when she applies for credit, but an UltraFICO score is only generated if the borrower opts in to share her account information.

3   Preliminary Analysis: Credit Market Competition

This section characterizes the equilibrium for credit market competition. This analysis is a building block for our study of the impact of open banking in the next section. To make the analysis applicable to both the situations before and after open banking, we consider an identity-neutral case where a strong lender with screening ability x_s and a weak lender with screening ability $x_w < x_s$ compete for a borrower whose prior credit quality is τ. In our model, the bank is the strong lender before open banking, but the fintech becomes the strong lender after open banking, *if* the borrower chooses to share her banking data. Open banking can also influence beliefs about the borrower's credit quality τ since lenders may revise their beliefs based on the borrower's sign-up decision.

When (1) fails for both lenders, there is no lending and the market is inactive; when (1) fails for the weak lender, the strong lender will simply act as a monopolist and charge the highest possible interest rate $\bar{r}$ upon seeing a good signal. In the rest of this section, we

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

study the more interesting case when (1) holds for both lenders.

For notational convenience, let

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

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

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

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

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

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

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

the probability of the opposite event. In either case, the expected repayment probability is zero.

Notice first that the credit market competition in our model has the flavor of common-value auctions. A lender wins a borrower if it offers a lower interest rate than its rival, or if the rival rejects the borrower after seeing a bad signal. In the latter case, the lender suffers from a winner's curse by serving a low-type borrower. As a well-known result in the literature, there is no pure-strategy equilibrium due to this winner's curse.[22]

3.1 Mixed-Strategy Equilibrium

The characterization of the mixed-strategy equilibrium is standard (see, e.g., similar analyses in Broecker (1990); Hauswald and Marquez (2003)). Let m_j, $j \in \{s, w\}$, be the probability that lender j makes an offer to a borrower upon seeing a good signal. (As we will see, in the

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[22]In any pure-strategy equilibrium, it is impossible that the two lenders offer different interest rates upon seeing a good signal; otherwise the lender offering a lower interest rate could always raise its interest rate slightly without losing any demand. If they charge the same interest rate r upon seeing a good signal, the strong lender, say, makes a profit $0.5 \times p_{HH}\left[\mu_{HH}\left(1 + r\right) - 1\right] - p_{HL}$, with 0.5 capturing a fair tie-breaking rule and p_{HL} reflecting the winner's curse. Whenever this profit is positive, the first portion must be strictly positive, in which case the strong lender will have a unilateral incentive to undercut its opponent.

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

In a mixed-strategy equilibrium,[23] the strong lender's indifference condition is

$$p_{HH}\left[1 - m_w + m_w\overline{F}_w(r)\right]\left[\mu_{HH}(1+r) - 1\right] - \underbrace{p_{HL}}_{\text{winner's curse}} = \pi_s. \qquad (3)$$

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

$$p_{HH}\left[1 - m_s + m_s\overline{F}_s(r)\right]\left[\mu_{HH}(1+r) - 1\right] - \underbrace{p_{LH}}_{\text{winner's curse}} = \pi_w. \qquad (4)$$

Notice that $p_{LH} > p_{HL}$ given $x_s > x_w$. The weak lender thus faces a severer winner's curse and so a higher lending cost—i.e., it is more likely for the weak lender to make a wrong decision and lend to a low-type borrower. Given that there is no product differentiation, as we show in the appendix, only the strong lender with a lower lending cost makes a positive profit (i.e., $\pi_s > 0$ and $\pi_w = 0$ in equilibrium). This also implies that the strong lender always makes an offer upon seeing a good signal (i.e., $m_s = 1$), and to sustain an equilibrium the weak lender has to participate and lend sometimes (i.e., $m_w \in (0, 1)$) though it makes a zero expected profit.

Define

$$\phi(r) \equiv \frac{p_{LH}}{p_{HH}\left[\mu_{HH}(1+r) - 1\right]} = \frac{x_s}{\frac{\tau}{1-x_w}r - 1 + x_s}, \qquad (5)$$

---

[23]It is routine to show that the mixed-strategy equilibrium behaves well. All the details can be found in the working paper version of this paper (NBER WP28118).

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and let

$$\Delta \equiv x_s - x_w$$

be the gap in screening ability between the two lenders. Then the mixed-strategy equilibrium is described as follows:[24]

Proposition 1. *When (1) holds for both lenders, 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 $\lambda_s = \phi(\overline{r}) \in (0,1)$ at $\overline{r}$; and*

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

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

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

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

$$F_s(r) = m_w F_w(r). \tag{6}$$

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

---

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

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.

Another useful observation is that when the strong lender's screening ability x_s improves, or the weak lender's screening ability x_w deteriorates, or the prior credit quality τ decreases, $\phi(r)$ becomes larger. This implies a relaxed lending competition where both lenders charge a higher interest rate in the sense of FOSD.

3.2   Borrower Surplus

For our subsequent analysis, it is important to calculate the surplus of each type of borrower, and investigate how they are affected by the prior credit quality τ and each lender's screening ability. Denote by $V_i\left(x_w, x_s, \tau\right)$ the expected surplus of an i-type borrower, $i \in \{h, l\}$, as a function of the two lenders' screening abilities and the prior credit quality.

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

$$(1 - m_w)\,\mathbb{E}\left[r_s\right] + m_w \mathbb{E}\left[\min\left(r_w, r_s\right)\right] = \underline{r} + \left(\overline{r} - \underline{r}\right)\phi\left(\overline{r}\right), \tag{7}$$

where $\phi\left(\cdot\right)$ is defined as in (5). 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 $\mathbb{E}\left[r_s\right] = \underline{r} + \int_{\underline{r}}^{\overline{r}}\overline{F}_s\left(r\right)dr$ and $\mathbb{E}\left[\min\left(r_w, r_s\right)\right] = \underline{r} + \int_{\underline{r}}^{\overline{r}}\overline{F}_s\left(r\right)\overline{F}_w\left(r\right)dr$.) Then a high-type borrower's expected surplus is

$$V_h\left(x_w, x_s, \tau\right) = \left(\overline{r} - \underline{r}\right)\left(1 - \phi\left(\overline{r}\right)\right), \tag{8}$$

which equals the high-type's pecuniary payoff from the project $\overline{r}$ net of the expected interest rate in (7). (Recall that we have normalized the high-type's nonmonetary benefit from getting a loan to zero.)[25]

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

---

[25]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 a consumer and she uses the loan to buy some goods for a utility u, we have assumed an interest rate cap $\overline{r}$, in which case the expected surplus is $V_h\left(x_w, x_s, \tau\right) = u - \underline{r} - \left(\overline{r} - \underline{r}\right)\phi\left(\overline{r}\right) = u - \overline{r} + \left(\overline{r} - \underline{r}\right)\left(1 - \phi\left(\overline{r}\right)\right).$ Since $u - \overline{r}$ is a constant, our analysis below carries over to this interpretation as well.

signal but does not make an offer. This occurs with probability $x_s\left[x_w + (1 - x_w)(1 - m_w)\right]$. Therefore, given $m_w = 1 - \phi(\bar{r})$, a low-type borrower's expected surplus is

$$V_l(x_w, x_s, \tau) = \delta\left[1 - x_s\left(x_w + (1 - x_w)\phi(\bar{r})\right)\right], \tag{9}$$

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

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

The first part is straightforward: a higher average credit quality lessens the winner's curse and so intensifies competition and benefits both types of borrowers. In particular, when τ goes to ∞ (i.e., when there is no default risk in the market), one can easily check from Proposition 1 that the equilibrium smoothly converges to the Bertrand outcome where both lenders offer a zero interest rate.

As for the second part, a change in screening ability brings about an "information" effect that changes the screening efficiency, and also a "strategic effect" that affects the degree of lender competition. When x_s is higher, low types are more likely to be detected and so get hurt; at the same time, the screening ability gap Δ widens, which softens competition and hurts both types of borrowers.[26] On the other hand, when x_w is improved, screening efficiency improves but competition intensifies as the ability gap Δ shrinks. The high types benefit from both effects, but the low types can be ambiguously affected by these competing forces.

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. 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.

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[26]The improved screening efficiency from a higher x_s has no effect on the high types, as the strong lender absorbs all the rent by enjoying a higher profit.

Corollary 1. *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.*

4 The Impact of Open Banking

We now investigate the welfare impacts of open banking. Our main research question is whether open banking, which intends to promote competition and benefit consumers as advocated, instead can have a perverse effect and harm borrowers even if they can choose whether to share their data. In other words, we are interested in whether *both* types of borrowers could get worse off due to open banking. Relative to other welfare criteria (say, total surplus; see discussions in footnotes 18 and 28), our approach is more practically relevant to regulators whose mission mainly concerns consumer protection and financial inclusion (e.g., the Financial Conduct Authority that regulates open banking in the United Kingdom).

To make our analysis transparent, we will first consider the hypothetical case in which data sharing is mandatory (i.e., the data will be shared *without* customers' consent). We will then turn to the case in practice with voluntary sign-up where the aforementioned channel of credit quality inference from sign-up decisions plays an important role. We focus on the most interesting case when (1) holds for both lenders—i.e., when both of them are active before open banking.[27]

4.1 Mandatory Sign-Up

Suppose now that all borrowers are required to sign up for open banking. Therefore, for any borrower, the fintech's screening ability improves to $x'_f > x_b$. Since such a mandatory sign-up does not cause any market segmentation, both lenders' belief about a borrower's credit quality remains τ before a creditworthiness test. Let $V_i\left(x_b, x'_f, \tau\right)$ be the expected surplus

---

[27]If (1) fails for both lenders, we have a trivial case as the lending market collapses before open banking. The case when (1) holds for the bank but fails for the fintech is also relatively straightforward. Before open banking, the bank is a monopolist and charges the highest interest rate $\bar{r}$ upon seeing a good signal, delivering a zero surplus to the high type. Therefore, open banking must benefit the high type by introducing competition (if borrowers choose to share their data). The impact of open banking on the low type is slightly trickier: with an active fintech, they have an additional chance to be perceived as high type (which benefits them), but meanwhile the bank, now as the weak lender, sometimes does not extend an offer to them even upon seeing a good signal. For instance, if the fintech's screening ability becomes sufficiently high after open banking, then the first effect is negligible and the second effect dominates, yielding a lower payoff to the low type.

of a borrower of type $i \in \{h, l\}$ after open banking. (Recall that the first dependent variable in the borrower surplus function is the weak lender's screening ability.) The main message from this section, as reported in the proposition below, is that if all borrowers share their data under open banking, this will most likely improve industry profit and harm borrowers assuming open banking significantly enhances the fintech lender's screening ability.

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

1. *open banking with mandatory data sharing helps the fintech but harms the bank, and it improves industry profit if and only if it widens the screening ability gap between the lenders (i.e., if $\Delta' > \Delta$);*

2. *for a fixed $x_b < 1$, there exist $\tilde{x}_f < x_b < \tilde{x}'_f$ such that open banking with mandatory data sharing harms all borrowers if $x_f \in [\tilde{x}_f, x_b]$ and $x'_f \geq \tilde{x}'_f$; whenever open banking harms all borrowers, it improves industry profit and market efficiency (if a low-type borrower generates an efficiency loss whenever she gets a loan).*

The impact of mandatory open banking on lender profit is straightforward: 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 $\Delta' > \Delta$.

The impact on borrower surplus is less straightforward. Open banking benefits borrowers of type i if and only if $V_i\left(x_b, x'_f, \tau\right) > V_i\left(x_f, x_b, \tau\right)$. Proposition 2 implies that for a fixed x_b, (i) V_h increases in $x_f < x_b$ but decreases in $x_f > x_b$, and (ii) V_l can vary with $x_f < x_b$ nonmonotonically but must decrease in $x_f > x_b$. Figure 2 below depicts a numerical example of how V_h (Panel A) and V_l (Panel B) vary with x_f for $x_b = 0.35$.

Therefore, as revealed by Figure 2, if x_f is sufficiently close to x_b before open banking and x'_f is sufficiently greater than x_b after open banking, both types of borrowers suffer due to open banking. In other words, mandatory open banking is detrimental to all borrowers if it causes a new, sufficiently larger asymmetry between lenders.

It is also useful to think of the borrower surplus problem from the perspective of the base screening ability x_w and the ability gap Δ as in Corollary 1. Open banking improves the base screening ability, which benefits the high-type but harms the low-type. Hence, the high-type will suffer due to open banking only if it widens the gap (i.e., if $\Delta' > \Delta$), in which case the low-type must suffer due to open banking and industry profit must increase.

Figure 2: Borrower Surpluses when Fintech Screening Ability x_f Varies
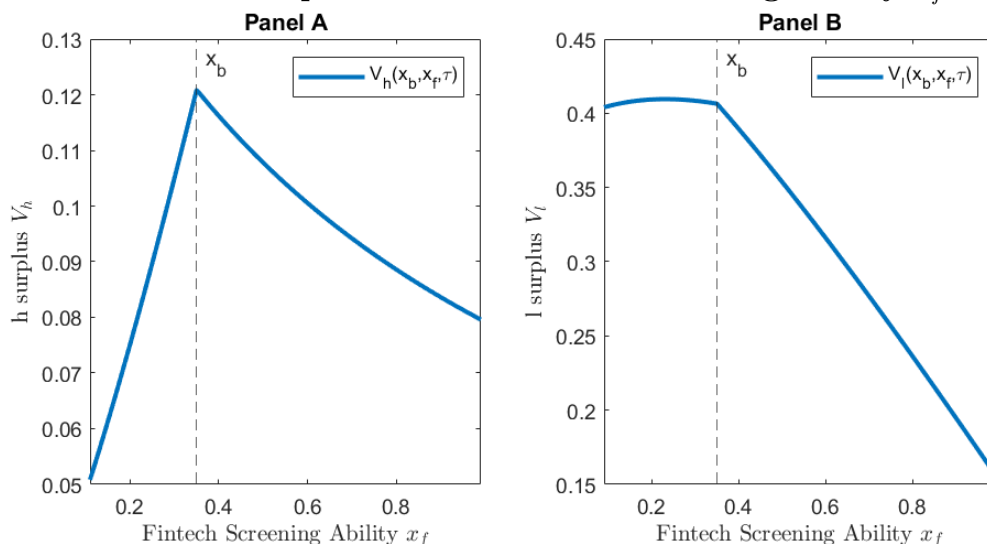
High-type borrower surplus (Panel A) and low-type borrower surplus (Panel B). We plot the borrower surplus of both types as functions of the fintech lender's screening ability x_f. The high-type borrower surplus $V_h(x_b, x_f, \tau)$ has a single peak at $x_f = x_b$, while $V_l(x_b, x_f, \tau)$ is hump-shaped in the range of $x_f < x_b$. Parameter values are $\bar{r} = 0.36$, $x_b = 0.35$, $\delta = 0.5$, and $\tau = 3.4$.

To understand the result concerning market efficiency, notice that in our setup high-type borrowers always get a loan in either regime, implying that open banking is efficiency neutral to these borrowers. Low-type borrowers' surplus is proportional to the chance that they get a loan, and so whenever they suffer due to open banking, it must be that these low-type borrowers are less likely to get a loan (which improves the aggregate surplus if the low-type's private benefit from receiving a loan is below the loan cost, i.e., $\delta < 1$).[28]

Although we have focused on the potential perverse effect of open banking on borrowers, it is clear that if open banking only enhances the fintech's screening ability moderately, it can benefit one or both types of borrowers. For instance, if x_f is sufficiently lower than x_b while x'_f is close to x_b, high-type borrowers benefit from mandatory sign-up, and in this case low-type borrowers benefit as well if $V_l(x_f = 0, x_b, \tau) < V_l(x_f = x_b, x_b, \tau)$ as in Figure 2.

---

[28]In this case of $\delta < 1$, denying loans to low type is beneficial from the perspective of total surplus. We do not take a stand in this aggregate welfare issue, which is more relevant when a redistribution tool is allowed. Instead, we take a more "positive" approach to study how each type of borrower is affected by open banking, which is more relevant to regulators with consumer protection as the main goal.

4.2   Voluntary Sign-Up

A prominent feature in the practice of open banking regulation is to allow borrowers to decide by themselves whether to share their banking data with new lenders. With this voluntary sign-up design, people may think that open banking can never harm borrowers. However, we argue that this view is not always true as borrowers' sign-up decisions may reveal information about their credit quality and so influence the lenders' pricing strategies.

4.2.1   Sign-up decisions and equilibrium characterization

Recall that in our model a fraction ρ of borrowers are privacy conscious and never sign up for open banking. So the sign-up decision is meaningful only for the remaining $1-\rho$ non-privacy-conscious borrowers. Let $\sigma_i \in [0,1]$, $i \in \{h,l\}$, be the fraction of i-type non-privacy-conscious borrowers who choose to sign up for open banking.

Given that a borrower's sign-up decision is observable to both lenders, 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 the lenders' updated priors on the credit quality in the two market segments respectively. Specifically,

$$
\begin{cases}
\tau_+ \equiv \dfrac{\Pr[h \mid \text{sign up}]}{\Pr[l \mid \text{sign up}]} = \dfrac{\theta(1-\rho)\sigma_h}{(1-\theta)(1-\rho)\sigma_l} = \tau \cdot \dfrac{\sigma_h}{\sigma_l} \\[2mm]
\tau_- \equiv \dfrac{\Pr[h \mid \text{not sign up}]}{\Pr[l \mid \text{not sign up}]} = \dfrac{\theta[\rho+(1-\rho)(1-\sigma_h)]}{(1-\theta)[\rho+(1-\rho)(1-\sigma_h)]} = \tau \cdot \dfrac{1-(1-\rho)\sigma_h}{1-(1-\rho)\sigma_l}
\end{cases},
\tag{10}
$$

Intuitively, when high-type non-privacy-conscious 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 privacy-conscious 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 non-privacy-conscious borrower of type i is governed by:

$$
\begin{cases}
\sigma_i = 1, & \text{if } V_i\left(x_b, x_f', \tau_+\right) > V_i\left(x_f, x_b, \tau_-\right), \\[1mm]
\sigma_i \in [0,1], & \text{if } V_i\left(x_b, x_f', \tau_+\right) = V_i\left(x_f, x_b, \tau_-\right), \\[1mm]
\sigma_i = 0, & \text{if } V_i\left(x_b, x_f', \tau_+\right) < V_i\left(x_f, x_b, \tau_-\right).
\end{cases}
\tag{11}
$$

If a borrower chooses to sign up, she will be classified in the market segment characterized by

$\left(x_b, x'_f, \tau_+\right)$ where the fintech becomes the strong lender; otherwise, she will be classified in the market segment characterized by (x_f, x_b, τ_-) where the fintech remains the weak lender. Note also that the surplus of an i-type privacy-conscious 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 non-privacy-conscious borrowers described in (11), (ii) $\{\tau_+, \tau_-\}$ are the lenders' updated priors on the average credit quality in each market segment as determined in (10), 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 of credit quality in that segment becomes so low that condition (1) fails to hold for that lender. In that case, the pricing equilibrium and the expressions for borrower surplus need to be modified but in a straightforward way. Second, if the lenders expect sign-up decisions $\sigma_l = 0$ and $\sigma_h > 0$, then they will regard any borrower who signs up as a high type. In this case, we assume that a creditworthiness test will still be conducted, and if a lender observes a bad signal, it will reclassify the borrower as low type.[29]

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

The following lemma helps narrow down the possible types of equilibria. 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 also plays an important role in generating the perverse effect for open banking as discussed below in Section 4.2.2.

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

Lemma 1. *If low-type non-privacy-conscious borrowers weakly prefer to sign up for open banking, then high-type non-privacy-conscious borrowers must strictly prefer to do so.*

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

Proposition 4. *In the regime of open banking with voluntary sign-up, there exists a unique nontrivial equilibrium. It falls into three possible types:*

1. *If $V_l\left(x_f, x_b, \tau\right) \leq V_l\left(x_b, x'_f, \tau\right)$, the equilibrium is pooling: all non-privacy-conscious borrowers sign up for open banking regardless of their credit quality (i.e., $\sigma_l = \sigma_h = 1$).*

2. *If $V_l\left(x_f, x_b, \tau\right) > V_l\left(x_b, x'_f, \tau\right)$ and $V_l\left(x_f, x_b, \rho\tau\right) < V_l\left(x_b, x'_f, \infty\right)$, the equilibrium is semi-separating: an endogenous fraction of low-type non-privacy-conscious borrowers and all high-type non-privacy-conscious borrowers sign up (i.e., $\sigma_l \in (0, 1)$ and $\sigma_h = 1$).*

3. *If $V_l\left(x_f, x_b, \rho\tau\right) \geq V_l\left(x_b, x'_f, \infty\right)$, the equilibrium is separating: low-type non-privacy-conscious borrowers never sign up, while high-type non-privacy-conscious borrowers always sign up (i.e., $\sigma_l = 0$ and $\sigma_h = 1$).*

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

In the pooling equilibrium (Proposition 4.1), if low-type borrowers benefit from open banking when the prior of credit quality remains unchanged, high-type borrowers must benefit as well. Then it must be an equilibrium in which all non-privacy-conscious borrowers sign up. In the separating equilibrium (Proposition 4.3), the condition implies that low-type borrowers will never sign up: they do not want to even if the credit quality inference becomes the most favorable for opting-in.[30] 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 $\bar{r}$.

In the semi-separating equilibrium (Proposition 4.2), notice that Lemma 1 has shown that all high-type non-privacy-conscious borrowers will sign up in any equilibrium where some low types sign up. Given this, if all low-type non-privacy-conscious borrowers also sign up,

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

then the priors on credit quality in both market segments remain unchanged ($\tau_+ = \tau_- = \tau$). Therefore, the first condition $V_l\left(x_f, x_b, \tau\right) > V_l\left(x_b, x'_f, \tau\right)$ implies that they actually would like to opt out. If none of the low-type non-privacy-conscious borrowers sign up, the prior on credit quality in the opt-in market becomes the most favorable, in which case the second condition $V_l\left(x_f, x_b, \rho\tau\right) < V_l\left(x_b, x'_f, \infty\right)$ implies that they actually would like to join the opt-in market. As a result, in this case low-type non-privacy-conscious 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 privacy-conscious borrowers (i.e., $\rho > 0$) in our model. If $\rho = 0$, we must have $\tau_- = 0$ in any nontrivial 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 nontrivial equilibrium is the pooling equilibrium where all borrowers sign up and the outcome is the same as with mandatory sign-up.[31] This is certainly not what we observe in the real market, and introducing some privacy-conscious borrowers makes our model not only richer but also better at matching the practice. Moreover, as we will see shortly, having some privacy-conscious borrowers (i.e., $\rho > 0$) tends to mitigate the perverse effect of open banking we are after, so that we do not overclaim the possibility of the perverse effect.

4.2.2 The impact of open banking

We now examine the impact of open banking with voluntary sign-up:

Proposition 5. *Compared to the regime before open banking,*

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

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

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[31]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.

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

The result in the case of the pooling equilibrium is straightforward. In the separating equilibrium, opting-in reveals high type, while opting-out signals worse credit quality than average $\tau_- = \rho\tau < \tau$. Hence, open banking benefits only the high-type non-privacy-conscious borrowers (who enjoy a zero interest rate in a Bertrand outcome in the opt-in market without any winner's curse), and hurts all other borrowers who opt out.

The second result in the semi-separating equilibrium points to the perverse effect of open banking. For borrowers who opt out, they must get worse off from the unfavorable inference $\tau_- < \tau$. For low-type non-privacy-conscious borrowers who sign up, since they are indifferent about signing up, they must get worse off as well. For high-type non-privacy-conscious borrowers, although they are viewed more favorably ($\tau_+ > \tau$), they might face softened competition if the fintech's screening ability improves too much and so could also suffer due to open banking. More precisely, all borrowers suffer due to open banking if and only if the following conditions are satisfied:

$$V_h\left(x_f, x_b, \tau_-\right) \leq V_h\left(x_b, x_f', \tau_+\right) < V_h\left(x_f, x_b, \tau\right), \tag{12}$$

and

$$V_l\left(x_f, x_b, \tau_-\right) = V_l\left(x_b, x_f', \tau_+\right), \tag{13}$$

where $\tau_- = \frac{\rho\tau}{1-(1-\rho)\sigma_l} < \tau < \tau_+ = \frac{\tau}{\sigma_l}$ as we have $\sigma_h = 1$ in the semi-separating equilibrium. These conditions ensure the semi-separating equilibrium, with the second inequality in (12) as the extra condition for high-type non-privacy-conscious borrowers to become worse off. We show in the proof of Proposition 5 that there exist parameter configurations which satisfy both (12) and (13).

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

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Voluntary vs. mandatory sign up. As both V_h and V_l increase in the prior credit quality, conditions (12) and (13) can hold only if $V_h\left(x_b, x'_f, \tau\right) < V_h\left(x_f, x_b, \tau\right)$ and $V_l\left(x_b, x'_f, \tau\right) < V_l\left(x_f, x_b, \tau\right)$, i.e., only if all borrowers suffer due to open banking in the case of 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.

The information externality to non-privacy-conscious borrowers Another interesting observation is that privacy-conscious borrowers *always* (weakly) suffer due to open banking with voluntary sign-up. Again, this is due to the adverse inference in the opt-out market (Lemma 1): in the pooling equilibrium they remain unaffected, while in the other two equilibria they get strictly worse off. The selection behavior of the non-privacy-conscious borrowers imposes a negative externality on the privacy-conscious borrowers. This observation complements Aridor, Che, and Salz (2020) in that whoever embraces the new technology exerts a negative externality on those who are left behind.

4.2.3 Numerical analysis: Equilibrium and perverse effect

Figure 3 below provides a numerical example that illustrates different types of equilibria and the possibility of the perverse effect of open banking. We fix the lenders' screening abilities (which permit a relatively large screening ability gap after open banking), but vary both the prior credit quality now measured by θ (i.e., the fraction of high-type borrowers in the market, and we focus on the range such that Assumption 1 holds) and the fraction of privacy-conscious borrowers ρ.

When the credit quality $\theta = \frac{\tau}{1+\tau}$ is high and more borrowers are privacy conscious (i.e., ρ is high), opting-out does not result in a significant deterioration in credit quality inference, so the separating equilibrium arises in which low types opt out, as shown on the upper-right corner with blue dash-dotted boundaries in Figure 3. When the credit quality θ decreases, we enter the region with red solid boundaries, where a semi-separating equilibrium arises and low types are just indifferent about sign-up decisions. To the right of the red dashed line, θ is still sufficiently high that the inferred credit quality in the opt-out market segment is not too low and both lenders are active there. To the left of the red dashed line, however, θ becomes sufficiently low and the inferred credit quality in the opt-out market segment is such that the fintech lender quits that market. (Under the specific parameter configuration

Figure 3: Voluntary Sign-Up Equilibrium
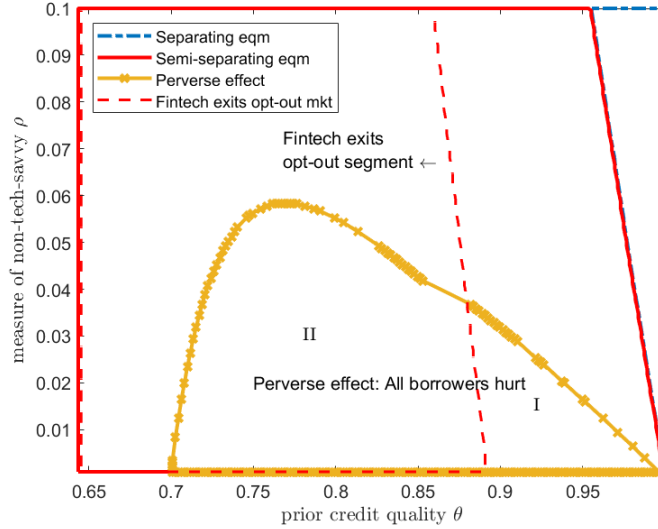
(Nontrivial) voluntary sign-up equilibrium in the parameter space of $\left(\theta = \frac{\tau}{1+\tau}, \rho\right)$ when $\bar{r} = 0.36$, $x_b = 0.4$, $x_f = 0.35$, and $x_f' = 0.8$. (We focus on the range of θ such that Assumption 1 holds for both lenders.) The blue dashed-line region features the separating equilibrium, while the red solid-line region features the semi-separating equilibrium. (There is no pooling equilibrium in this example.) In the region of semi-separating equilibrium, the red dashed line illustrates a transition of lender participation in the opt-out segment: the fintech becomes inactive since θ lies to the left of this line. In the yellow crossed-line region, both types of borrowers are hurt by open banking despite voluntary sign-up.

in Figure 3, there is no pooling equilibrium.)

The yellow crossed lines depict the region where the perverse effect of open banking arises. The effect of ρ is straightforward: the smaller the fraction of privacy-conscious borrowers, the more sensitive the credit quality inference based on the sign-up decisions; this sensitivity creates room for the perverse effect even when borrowers control the information. In region I with a relatively high θ, the perverse effect is due to the adverse inference (in the opt-out market) and the relaxed competition (in the opt-in market). In region II with a relatively low θ, condition (1) fails to hold for the fintech in the opt-out segment. The consequence of fintech exiting from the opt-out segment further strengthens the perverse effect.[32] Similar patterns as in Figure 3 arise for many other parameter configurations where $\Delta' > \Delta$.

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[32]More precisely, in response to the inactive fintech in the opt-out market, a larger fraction of low types sign up for open banking so that they are still indifferent in equilibrium. The chain reaction is that this makes non-privacy-conscious high types suffer more from open banking, as they are pooled with more low types and the effect of softened competition dominates.

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The main message from this numerical analysis, which is relevant to policy making, is that the perverse effect of open banking most likely occurs in the market where relatively few borrowers are very privacy conscious (small ρ), and the credit quality τ is not too high (so that the fintech may exit in the opt-out segment). Though the second point regarding τ applies to both applications of consumer credit and small business loans, the first point on ρ seems to imply that the perverse effect is more likely to occur in the market for small business loans (where noneconomic privacy concerns are less severe).

5   Robustness Discussions and Extensions

This section first discusses whether our main insight concerning the perverse effect of open banking is robust to various extensions. It then discusses a comparison between the regulation approach and the free-market approach for open banking.

5.1   Fintech Affinity

Besides algorithmic screening, customers and lenders interact differently in fintech lending. Automated processing not only makes fintech loans more swift, involving less steps and quicker approval decisions (e.g., Fuster, Plosser, Schnabl, and Vickery, 2019), but also allows for niche products such as tailored financing options (like "Buy Now Pay Later"), platform-based lending (e.g., SoFi provides one-shop-for-all services), and small business loans based on payment network (e.g., Square loans are automatically repaid by sales). All these business practices imply that fintech lenders may enjoy certain monopoly power over at least some borrowers thanks to their ability to provide better or tailored services (e.g., Buchak, Matvos, Piskorski, and Seru, 2018).

In our baseline model, open banking creating a sufficiently large gap in screening abilities is necessary for the perverse effect to emerge. More precisely, from Section 4.2.2 we know that for the perverse effect to arise, it is crucial that high-type borrowers suffer due to signing up for open banking. This can happen only if the widened screening ability gap reduces the high type's surplus under open banking with mandatory sign-up. In this extension we show that this tends to occur more when borrowers exhibit affinity toward fintech loans.

There are many possible ways to introduce fintech affinity; the following setting involves minimal modifications to our baseline while still capturing the essence of fintech affinity. Suppose now that each borrower is subject to a preference shock ex post: when she has

offers from both the bank and the fintech, with a probability $\xi \in [0, 1)$ she will only consider the fintech's offer—regardless of the details of the bank offer. For simplicity, we call this preference shock a ξ-event, and later refer to ξ as fintech affinity. This preference shock, however, is irrelevant if a borrower only receives an offer from the bank, in which case she will take the offer provided its interest rate is no greater than $\bar{r}$.

One potential interpretation of the ξ-event is that bank loan processing takes a lot of time and the borrower becomes impatient. (For instance, in the ξ-event, a borrower receives a utility of $\epsilon \cdot (\bar{r} - r_b)$ from the bank loan, where $\epsilon \to 0$ reflects the impatient borrower's prohibitively high discount rate.) More broadly, these borrowers hit by the preference shock are similar to the "captured" consumers in Varian (1980), which gives the fintech local monopoly power. For simplicity, we assume that the ξ-event is independent of a borrower's credit quality and is unobservable to both lenders. (Section 5.2 considers the case where this observability is affected by open banking.)

We focus on the relatively simple case where the fintech still earns a zero profit and the bank makes a positive profit before open banking; the precise condition for this is derived below. As in Section 3, the bank's indifference condition is

$$p_{HH} \left[1 - m_f + m_f (1 - \xi) \overline{F}_f (r) \right] \left[\mu_{HH} (1 + r) - 1 \right] - p_{HL} = \pi_b, \tag{14}$$

where m_f is the probability that the fintech makes an offer upon seeing a good signal. Compared to (3), the only difference here is that when both lenders make offers to a borrower, the bank will win the competition only with probability $1 - \xi$ even if its offer is better. The terms of winner's curse, however, are unaffected by the preference shock since the fintech does not make an offer anyway upon seeing a bad signal. Therefore, fintech affinity hurts the bank competing for a potentially profitable borrower but never helps it avoid lemons and mitigate the winner's curse.

The fintech's indifference condition, given that the bank always makes an offer upon seeing a good signal, is

$$p_{HH} \left[\xi + (1 - \xi) \overline{F}_b (r) \right] \left[\mu_{HH} (1 + r) - 1 \right] - p_{LH} = 0. \tag{15}$$

Compared to (4) with $m_s = 1$, the only difference here is that the fintech now has an additional chance to win a borrower due to fintech affinity. Therefore, fintech affinity alleviates the fintech's competitive disadvantage from its lower screening ability.

As in Section 3, from the indifference conditions it is easy to derive

$$\pi_b = \frac{1-\xi}{1-\xi\phi(\overline{r})}p_{LH} - p_{HL},$$

where $\phi(r) = \frac{P_{LH}}{P_{HH}[\mu_{HH}(1+r)-1]}$, as defined in (5). For π_b to be positive, we need

$$\frac{1-\xi}{1-\xi\phi(\overline{r})} > \frac{p_{HL}}{p_{LH}} = \frac{x_f(1-x_b)}{x_b(1-x_f)}. \tag{16}$$

This holds if x_f is sufficiently lower than x_b. In particular, for a given $\xi > 0$, this requires $x_f < \hat{x}_f$, where $\hat{x}_f < x_b$ solves the equality of (16). (When $\xi = 0$, we have $\hat{x}_f = x_b$ and so return to the baseline case.)

When condition (16) fails to hold, which includes the case with $x_f > x_b$ after open banking, the situation gets more complicated. However, there must exist an equilibrium with $\pi_b = 0 < \pi_f$ as characterized in Online Appendix C.1.

Let $V_h(x_f; \xi)$ be the expected surplus of a high-type borrower as a function of fintech screening technology x_f given fintech affinity ξ, where we have omitted other dependent variables. Then we prove the following result in Online Appendix C.1:

Lemma 2. *Let $\hat{x}_f$ solve the equality of (16) and satisfy $\hat{x}_f < x_b$. We have:*

1. *In the range of $x_f < \hat{x}_f$, $V_h(x_f; \xi)$ increases in x_f; in the same range, $V_h(x_f; \xi) > V_h(x_f; 0)$, so compared to the baseline case with $\xi = 0$, V_h becomes higher everywhere.*

2. *In the range of $x_f > \hat{x}_f$, $V_h(x_f, \xi)$ decreases in x_f; in the range of $x_f > x_b$, $V_h(x_f, \xi) < V_h(x_f, 0)$, so compared to the baseline case with $\xi = 0$, V_h becomes lower everywhere.*

The pattern of how V_h varies with x_f is the same as in the baseline model, except that now V_h peaks earlier than before given $\hat{x}_f < x_b$. The result concerning the comparison between $V_h(x_f; \xi)$ and $V_h(x_f; 0)$ is more important for our main result below. When $x_f < \hat{x}_f$, the fintech with a greater ξ is more willing to lend upon seeing a good signal. This induces the bank to compete more fiercely and so benefits borrowers. When $x_f > \hat{x}_f$, the fintech with a greater ξ charges a higher interest rate, which softens competition and harms borrowers.

Now consider the impact of open banking with mandatory sign-up, which improves the fintech's screening ability from x_f to $x'_f > x_b > x_f$. From Lemma 2, one can readily show that, if open banking with mandatory sign-up harms the high-type borrower in the baseline model with $\xi = 0$, i.e., if $V_h(x_f; 0) > V_h(x'_f; 0)$, then this must remain true given the

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fintech affinity $\xi > 0$, i.e., $V_h\left(x_f; \xi\right) > V_h\left(x_f'; \xi\right)$.[33] Intuitively, fintech affinity compensates the fintech's disadvantage in screening before open banking but complements its advantage in screening after open banking. As a result, it can only expand the lender asymmetry created by open banking and so exacerbate the perverse effect. Consequently, with the fintech affinity $\xi > 0$, there is a larger set of parameters for the high-type borrowers to suffer due to open banking with mandatory sign-up. As we have argued in the beginning of this section, this gives us more flexibility in looking for the perverse effect of open banking when sign-up becomes voluntary.

5.2 Preference Data and Targeted Loans

The data that modern financial institutions process are multidimensional and contain information not only on credit quality but also on other aspects of customer behavior. Such extra information can be particularly valuable for fintech companies given their more advanced "big data" technology, which could potentially hurt customers. Broadly related to consumer privacy, this category of information nicely complements the information on credit quality studied in Section 4.

Exactly because of such concerns, many regulators around the world mandate consent from customers themselves when sharing their data. This, however, cannot fully protect borrowers even if they control their own data, again because noncredit data sharing is intertwined with credit quality inference as we saw before.

The following discussions draw heavily on the working paper version of this paper (NBER WP28118), which takes the setting in Section 5.1 but changes the information content of open banking. Before open banking, the fintech cannot observe the ξ-event (i.e., a borrower's preference shock). As a borrower signs up for open banking, however, this ξ-event becomes perfectly observable to the fintech lender. It then knows exactly when a borrower is "locked in" to fintech loans, in which case it can exploit the borrower by charging a high interest rate.[34]

As in Section 5.1, we assume that in the ξ-event the borrower will only take fintech loans; this captures the fintech's "precision marketing," which combines the newly accessible

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[33]If $x_f < \hat{x}_f$, this result follows from $V_h\left(x_f; \xi\right) > V_h\left(x_f; 0\right) > V_h\left(x_f'; 0\right) > V_h\left(x_f'; \xi\right)$, where the first and third inequalities use the results concerning the comparison with the baseline case in Lemma 2. If $x_f \in (\hat{x}_f, x_b)$, the result follows from the observation in Lemma 2 that V_h decreases in x_f when $x_f > \hat{x}_f$.

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

banking transaction records with other existing information (e.g., the borrower's social media data).[35] To highlight the new information role of open banking, we assume that the fintech lender's screening ability on credit type remains unchanged (i.e., $x'_f = x_f$) after open banking. We then fully characterize the equilibrium outcome as a function of ξ, and show a similar welfare result as in Section 4: all borrowers may get hurt by open banking in equilibrium. This occurs for an intermediate probability of preference events. Intuitively, those who sign up suffer due to being exploited in the captured events; those who do not sign up instead suffer due to an unfavorable credit quality inference.

5.3   Multiple Fintech Lenders

We have adopted the simplest model structure with only two lenders to study credit market competition. This is consistent with the fact that search frictions often restrict the size of borrowers' consideration set.[36] However, open banking could substantially enlarge the consideration set (Clark, Houde, and Kastl, 2020) by alleviating search frictions and/or promoting inclusive financing. The number of lenders matters for our analysis, in that the perverse effect from sharing credit quality data crucially relies on softened competition after open banking. Therefore, a natural question is: will the potential perverse effect on borrowers vanish once there are multiple fintech lenders?

The number of lenders per se does not always matter for the perverse effect; in fact, in standard credit market competition models featuring information asymmetry, there will be at most two active lenders in equilibrium whenever lenders differ in screening abilities. Consider, for example, the case with three lenders—one bank and two fintechs. When the lenders differ in their screening abilities but offer homogeneous products, it is impossible for all three to survive (see Online Appendix C for a formal proof).[37] That is, before open banking, only the bank and the stronger fintech are active in the market; after open banking only the two fintechs with superior screening abilities are active. Hence, the perverse effect

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[35]This type of "precision marketing" captures two broad categories of situations. First, borrowers with a strong preference for "immediacy" prefer fintech loans; with open banking, the transaction records from the borrower's bank (which reveals the borrower's consumption habits), together with the borrower's digital footprint, may enable fintech lenders to better identify the borrowers' demand immediacy. Second, borrowers face a restricted set of available lenders in some circumstances (say, a borrower is traveling abroad and needs an emergency loan in foreign currency but unavailable from her bank).

[36]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.

[37]The winner's curse causing a barrier to entry is also familiar in the literature; see, e.g., Dell'Ariccia, Friedman, and Marquez (1999), Marquez (2002), and Rajan (1992).

still exists if the asymmetry between the two fintechs after open banking is sufficiently larger than that between the bank and the stronger fintech before open banking. This is likely to be the case, for example, if one fintech is a big-tech, like Ant Financial, while the other is a weaker start-up company in some niche market.

However, if the two fintechs are relatively similar, then the perverse effect will disappear. In Online Appendix C, we study the case of mandatory sign-up with one bank and two symmetric fintechs (both before and after open banking). In this special case, all three lenders are active before open banking, while the bank exits facing two stronger fintechs afterwards. The perverse effect is eliminated in this case. This is the most favorable situation from a regulator's perspective: improved screening ability increases total welfare, while the financial industry profits drop to zero, delivering a rising borrower surplus.

With voluntary sign-ups, the presence of multiple fintechs allow borrowers to strategically choose favorable fintechs with whom to share data, which significantly complicates the equilibrium analysis. However, high types may be discouraged from choosing certain fintechs due to equilibrium inference. This force makes the situation closer to our model with only two lenders.

5.4 The Laissez-Faire Approach to Open Banking

In some countries such as the U.S., the approach to open banking is more free market oriented, as we discussed in introduction. But how to incentivize traditional banks to share their customer data with fintech challengers, especially when the latter engage in competing business such as offering loans? One possibility is to allow banks to "sell" their data to fintechs.[38] Consider our baseline model but now assume that the bank can charge the fintech a fee (in the form of making a take-it-or-leave-it offer) if the latter wants to access a borrower's data (say, her transaction account record). Suppose the bank sets the fee uniformly across all borrowers with the same prior credit quality τ, and this data transaction occurs before the lenders conduct any credit test. In other words, the data fee is already a sunk cost when the lenders engage in credit competition. Then the credit market competition without the data transaction is the same as our baseline case before open banking, and that with the data transaction is the same as the competition under open banking.

Suppose first that the bank owns the data and borrowers have no control of whether to share their data. Since the bank can always extract the whole industry profit via the take-it-

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[38]Selling data is actually becoming a new business for traditional banks (see, e.g., https://bit.ly/3Gc8Wui).

or-leave-it offer, it is immediate to see from the analysis in Section 3 that the bank will sell its data at a price of $\frac{\Delta'}{1+\tau}$ if and only if $\Delta' > \Delta$ (in which case sharing the data improves industry profits). However, recall also that the perverse effect of open banking on borrowers can arise only if $\Delta' > \Delta$. Therefore, under the laissez-faire approach, data sharing does not happen when it could shrink the screening ability gap and intensify the lending competition, while it happens when it expands the gap and can adversely affect borrowers. In this sense, the laissez-faire approach tends to be less desirable for borrowers than the regulation approach.

Suppose now that borrowers own the data and the bank can sell a customer's banking data only with her consent. Consider the following timing: the bank first decides whether to make a take-it-or-leave-it offer to the fintech for the access to a borrower's banking data; if the offer is made, the borrower then decides whether to share her data; if the borrower approves the data transaction, the fee is paid by the fintech; a lending competition then takes place. If the bank does not sell the data, it makes a profit $\frac{\Delta}{1+\tau}$ from a borrower with credit quality τ. If it chooses to sell the data, how much will it charge the fintech? Since the fee is paid only upon receiving the borrower's consent, the fee should be equal to the fintech's profit from a borrower with updated prior credit quality τ_+, where τ_+ is the inferred credit quality in the opt-in market segment as we analyzed in Section 4.2. (Notice that the fee does not affect a borrower's data sharing decision and so has no impact on τ_+.) The fee should be therefore equal to $\frac{\Delta'}{1+\tau_+}$. As shown in Proposition 4, $\tau_+ \geq \tau$, and the strict inequality holds outside the region of a pooling equilibrium. This implies that we need an even higher $\Delta' > \frac{1+\tau_+}{1+\tau}\Delta$ than in the previous case to induce the bank to sell its data. That is, when borrowers control their banking data, data sharing arises only when it is even more adverse to borrowers (than in the previous case when the bank owns the data).

6 Conclusion

As the volume of data created by the digital world continues to grow, customer data have evolved into a defining force in every aspect of the banking business. As an integral part of the broader "open economy" initiative, open banking regulations require banks to share customers' data with third parties at customers' requests.

We offer the first theoretical study on how open banking affects credit market competition between traditional banks and fintech challengers when borrowers control their own data. Though consistent with the premise that open banking favors challenger fintechs, our results highlight that it may not always enhance competition and borrower welfare. Instead, we

show the existence of scenarios in which all borrowers are strictly worse off. Borrowers who sign up for open banking suffer due to a relaxed competition in the credit market, and borrowers who do not sign up suffer due to an adverse inference from their "sign-up" decisions. Broadly, the latter effect is consistent with the information externality caused by consumer decisions, an externality that poses a long-standing challenge to regulations on consumer protection in the modern financial industry.

There are some other important issues related to open banking that we leave for future research. For example, traditional banks operate not only in the lending market but also in the deposit and payment service markets. Open banking can affect their competition with fintech challengers in the latter markets as well. 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. Also, from a long-term perspective, should successful fintech giants also be required to share data back with traditional banks?

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A Proofs

A.1 Notation Summary

Table 1: Notation Summary

Notation	*Definition*	*Characterization*
θ, $\tau = \frac{\theta}{1-\theta}$	Probability and likelihood ratio of high-type	
ρ	Proportion of privacy-conscious borrowers	
δ_i, $i \in \{h, l\}$	Borrower's non-monetary benefit of receiving a loan	$\delta_h = 0, \delta_l = \delta > 0$
$V_i(x_w, x_s, \tau)$	Borrower i's surplus	
$S_j \in \{H, L\}$	Signal of lender $j \in \{b, f\}$, H or L	
x_j	Screening ability of lender j	$\mathbb{P}(S_j = L|l) = x_j$
x'_f	Screening ability of fintech after open banking	
$p_{HH}, p_{HL}, p_{LH}, p_{LL}$	Probability of lender signals	
$\mu_{HH}, \mu_{HL}, \mu_{LH}, \mu_{LL}$	Probability of repayment with given signals	
$r_j \in [\underline{r}, \bar{r}]$	Interest rate offered by lender j	$\bar{r}$ is exogenously given
m_j	Probability that lender j grants a loan given $S_j = H$	
$F_j(r); \overline{F}_j(r)$	CDF of r_j; survival function of $F_j(r)$	$\overline{F}_j(r) = 1 - F_j(r)$
λ_j	Mass point of $F_j(r)$ at $\bar{r}$	$\lambda_j = \lim_{r \uparrow \bar{r}} \overline{F}_j(r)$
π_j	Lender j's profit	
$\phi(r)$		Eq. (5)
Δ	Gap in screening ability	$\Delta = x_s - x_w$
σ_i, $i \in \{h, l\}$	Frction of type i non-privacy-concious opt-in borrowers	
τ_+, τ_-	Updated prior of borrowers opt-in (+) and opt-out (−)	
ξ	Probability of fintech affinity event	

A.2 Proof of Proposition 1

We first show a lemma:

Lemma 3. *In any mixed-strategy equilibrium, the strong lender makes a strictly positive profit* $\pi_s > 0$ *while the weak lender makes a zero profit* $\pi_w = 0$.

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

Suppose then $\pi_w \geq \pi_s = 0$. Then at $r = \underline{r}$, we must have $\overline{F}_w(r) = \overline{F}_s(r) = 1$, 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 $\pi_s > \pi_w = 0$. $\square$

Given that the strong lender makes a strictly positive profit, it must always make an offer upon seeing a good signal (i.e., $m_s = 1$). Equation (4) then simplifies to

$$p_{HH}\overline{F}_s(r)\left[\mu_{HH}(1+r) - 1\right] - p_{LH} = 0, \tag{17}$$

from which we solve $\overline{F}_s(r) = \phi(r)$. To make (17) hold for r close to $\bar{r}$, we need F_s to have a mass point at the top with a size of $\lambda_s \equiv \lim_{r\uparrow\bar{r}}\overline{F}_j(r) = \phi(\bar{r})$. (This also implies that the support of F_w must be open at the top.) From $\overline{F}_s(\underline{r}) = 1$, we solve $\underline{r} = \frac{1-x_w}{\tau}$, which is less than $\bar{r}$ when (1) holds.

Letting $r = \underline{r}$ in (3) yields $\pi_s = p_{LH} - p_{HL} = (1-\theta)(x_s - x_w) = \frac{\Delta}{1+\tau}$, and letting $r = \bar{r}$ in (3) yields $1 - m_w = \phi(\bar{r})$. Finally, $\overline{F}_w(r)$ is solved from (3).

A.3   Proof of Proposition 2

We first show how each lender's screening ability and the prior credit quality affect the degree of lending competition.

Lemma 4. *In the competition equilibrium,*

1. *when the screening ability gap Δ increases or the prior 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 weak lender's screening ability x_w deteriorates, or the prior 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.*

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

(ii) For any given $r \in [\underline{r}, \bar{r}]$, it is easy to see that $\phi(r)$ defined in (5) increases in x_s, decreases in x_w, and decreases in τ. So the claims follow immediately on the strong lender's interest rate distribution and the weak lender's probability of making an offer upon seeing a good signal. To see

the result concerning the weak lender's interest rate distribution, notice that the derivative of

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

with respect to x_s is proportional to $\tau r - (1 - x_w) \geq 0$. The inequality follows from $\underline{r} = \frac{1-x_w}{\tau}$. 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). $\qquad \square$

It is then easy to show Proposition 2. Result (i) is immediate from Lemma 4. A higher τ induces both lenders to offer lower interest rates (in the sense of FOSD) 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 Lemma 4. 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 Lemma 4 that interest rates go down and the weak lender is more likely to make offers upon seeing a good signal, and so the high-type must become better off. But now the weak lender is less likely to receive a high signal from screening a low-type borrower, and this negatively impacts the low-type borrowers. A straightforward calculation of the derivative of V_l with respect to x_w yields the cut-off result.

A.4 Proof of Corollary 1

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

$$V_h(x, \Delta, \tau) = \overline{r}\left(1 - \frac{1-x}{\overline{r}\tau}\right)[1 - \phi(\overline{r})], \tag{18}$$

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

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

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

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

This completes the proof.

A.5 Proof of Lemma 1

We prove the result by considering two cases.

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

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

and

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

When low-type borrowers weakly prefer to sign up, from V_l defined in (9) we know

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

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

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

and so

$$\phi_- (\bar{r}) > \phi_+ (\bar{r}). \tag{19}$$

Using the expression for the ϕ function, we have

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

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

$$\underline{r}_- > \underline{r}_+. \tag{20}$$

Then from (19), (20) and V_h defined in (8), we derive

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

i.e. the non-privacy-conscious high-type borrowers must strictly prefer to sign up.

(ii) Now consider the case when at least one lender is inactive in at least one market segment. First, suppose $\sigma_h \geq \sigma_l$. Then $\tau_+ \geq \tau$, so both lenders are active in the opt-in market and at least fintech (as the weak lender) is inactive in the opt-out market. Hence, our result holds because high-type borrowers strictly prefer to sign up and face two active lenders, rather than facing a

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monopolist bank or no active lenders at all. Second, suppose $\sigma_h < \sigma_l$. Then $\tau_- > \tau$ and so both lenders must be active in the opt-out market and at least the bank is inactive in the opt-in market. If the fintech is also inactive in the opt-in market, our result is of course true; if fintech is active, then the low-type must prefer the opt-out market where there are two active lenders with lower screening abilities.

A.6   Proof of Proposition 4

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

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

$$
V_l(x_f, x_b, \tilde{\tau}) = \begin{cases} 1 - x_b \left[x_f + (1 - x_f) \frac{x_b}{\frac{\tilde{\tau}\bar{r}}{1 - x_f} - (1 - x_b)} \right], & \text{if } \tilde{\tau}\bar{r} \geq 1 - x_f, \\ 1 - x_b, & \text{if } 1 - x_b < \tilde{\tau}\bar{r} < 1 - x_f, \\ (1 - x_b) m_b, & \text{if } \tilde{\tau}\bar{r} = 1 - x_b, \\ 0, & \text{if } \tilde{\tau}\bar{r} < 1 - x_b. \end{cases} \quad (21)
$$

(We have ignored δ, the size of the non-monetary benefit from getting a loan, as it is irrelevant for our analysis here.) The first case is when both lenders are active as analyzed in Section 3. Otherwise, fintech exits the opt-out market. In the second case, the bank always makes an offer at the monopoly interest rate $\bar{r}$ upon seeing a good signal (but recall that the low types only care about whether they get a loan). In the third case, the bank makes an offer (at $\bar{r}$) with probability $m_b \in [0,1]$ upon seeing a good signal (and makes zero profits), where m_b is pinned down in the corresponding equilibrium. In the last case, no lenders are willing to lend and so the surplus is zero.

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

$$\tau_-(\sigma_l) = \frac{\rho\tau}{1 - (1-\rho)\sigma_l} \leq \tau_+(\sigma_l) = \frac{\tau}{\sigma_l}. \tag{22}$$

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

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

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

$$V_l(x_f, x_b, \tau_-(\sigma_l)) = V_l(x_b, x'_f, \tau_+(\sigma_l)). \tag{23}$$

This is also a sufficient condition since Lemma 1 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 (23) 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 (23) 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 (23) is smaller when $\sigma_l = 0$. Moreover, the left-hand side $V_l(x_f, x_b, \tau_-(\sigma_l))$ as defined in (21) 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 equilibria.

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

Solving for $\sigma_l \in (0,1)$ in the semi-separating equilibrium. The exact equation that determines σ_l in (23) depends on how many lenders are active in the opt-out market. Let us first introduce two pieces of notation: let σ'_l solve

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

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

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

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

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

We need to deal with three cases separately:

(i) When $\rho\tau\bar{r} \geq 1 - x_f$, even if τ_- reaches its minimum $\rho\tau$, both lenders will be active in the opt-out market, and so $V_l(x_f, x_b, \tau_-)$ takes the standard form as in the first case of (21). Then (23) becomes

$$x_b[x_f + (1 - x_f)\frac{x_b}{\frac{\tau_-(\sigma_l)}{1-x_f}\bar{r} - 1 + x_b}] = x_f'[x_b + (1 - x_b)\frac{x_f'}{\frac{\tau_+(\sigma_l)}{1-x_b}\bar{r} - 1 + x_f'}], \tag{24}$$

where $\tau_-(\sigma_l)$ and $\tau_+(\sigma_+)$ are defined in (22).

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

$$x_b = x_f'[x_b + (1 - x_b)\frac{x_f'}{\frac{\tau_+(\sigma_l)}{1-x_b}\bar{r} - 1 + x_f'}]. \tag{25}$$

Otherwise, if $V_l(x_f, x_b, \tau_-(\sigma_l')) \leq V_l(x_b, x_f', \tau_+(\sigma_l'))$, then in equilibrium $\sigma_l \geq \sigma_l'$ and both lenders are active in the opt-out market, and σ_l solves the same equation (24) as in case (i). Also notice that in this case, $V_l(x_f, x_b, \rho\tau) = 1 - x_b < V_l(x_b, x_f', \infty) = 1 - x_b x_f'$, and so it is impossible to have the third type of separating equilibrium.

(iii) When $\rho\tau\bar{r} \leq 1 - x_b$, depending on the relationship between the equilibrium σ_l, σ_l', and σ_l'', the fintech may exit and the bank may randomly pass upon seeing good signal in the opt-out segment. Correspondingly, $V_l(x_f, x_b, \tau_-)$ could take the first three forms as in (21). 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 (24). If $V_l(x_f, x_b, \tau_-(\sigma_l'')) < V_l(x_b, x_f', \tau_+(\sigma_l''))$ but $V_l(x_f, x_b, \tau_-(\sigma_l')) > V_l(x_b, x_f', \tau_+(\sigma_l'))$, then the equilibrium $\sigma_l \in (\sigma_l'', \sigma_l')$, the fintech becomes inactive in the opt-out segment while the bank makes positive profits, so σ_l solves (25). If $V_l(x_f, x_b, \tau_-(\sigma_l'' + \epsilon)) > V_l(x_b, x_f', \tau_+(\sigma_l'' + \epsilon))$ for small $\epsilon > 0$, then the equilibrium $\sigma_l = \sigma_l''$, and still only the bank is active in the opt-out segment but it makes zero profit and randomly drops out upon seeing good signal.

A.7 Proof of Proposition 5

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

2. We only need to show that there is a nonempty set of primitive parameters such that (12) and (13) 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 that V_h decreases in the strong lender's screening ability and $x'_f > x_b$, the second inequality in (12) must hold if τ_+ is sufficiently close to τ. This is the case if σ_l is sufficiently close to 1.

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

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

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

Finally, we need (13) to hold for some parameters. The remaining parameter we can choose is x'_f. When $\tau_- \bar{r} = 1 - x_f$, one can check that $\frac{V_l(x_f, x_b, \tau_-)}{\delta} = 1 - x_b$. Then (13) requires

$$x_b = x'_f \left(x_b + (1 - x_b) \frac{x'_f}{\frac{\bar{r}\tau_+}{1-x_b} - 1 + x'_f} \right). \tag{26}$$

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 (26) exceeds x_b when $x'_f = 1$, and is less than x_b for some $\varepsilon > 0$ if $x'_f = x_b + \varepsilon$ given that $\bar{r}\tau > 1 - x_b$.) 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 (13) holds. This completes the proof. (Note that the parameters identified by this argument ensure that both lenders are active even in the opt-out market.)

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

$$\frac{n_+}{1 + \tau_+} + \frac{n_-}{1 + \tau_-} = \frac{1}{1 + \tau}. \tag{27}$$

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 (27).

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 (27), this is the case if $\Delta' > \Delta$, which must be true in our equilibrium where the high-type borrowers who sign up suffer due to open banking. (This is because from Corollary 1, we know that V_h increases in base screening ability and average credit quality but decreases in the ability gap. In the sign-up market segment, the base ability improves from x_f to x_b and the average credit quality improves from τ and τ_+, and so the high-type borrowers become worse off only if $\Delta' > \Delta$.)

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

B Open Banking: A Brief Overview

As we have mentioned in introduction, open banking is a series of reforms started in the U.K. related to how banks deal with customers' financial information, called for by the Competition and Markets Authority (CMA). Together with PSD2, all the regulated banks in the U.K. are mandated to enable customers to share their financial data—e.g., regular payments, credit card expenses, or savings statements—with authorized providers, including fintech companies, as long as customers give permission. 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."

In this brief overview of open banking, we first outline the Application Programming Interfaces (APIs) technology that underlies open banking. We then explain how open banking is affecting

the fintech sector and how it may disrupt the banking industry. Finally, we summarize the current status of open banking in practice, both in Europe and across the globe. Given the focus of paper, we organize this section with the theme of credit market development and competition.

Open Banking: API Besides other data security measures, the regulator sets up the open banking standard for APIs, which are intelligent conduits that allow for secure data sharing among financial institutions. With APIs, customers can connect their bank accounts to an app that can analyze their spending, recommend new financial products (e.g., credit cards), or sign up with a provider to display all of their accounts with multiple banks in one place.

There are two main ways, screen-scraping and APIs, by which third parties can access customers' data in practice. In screen-scraping, by giving providers "read-only" access to your online banking, you are giving them your login credentials and letting them pretend to be you. Screen-scraping is not as safe as API, through which 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, since programming facilitates customer control, APIs can allow access to only specific assets rather than your entire financial profile.

Investment management firms were among the early users of APIs, importing data on rates, fund performance, trade clearing and more from third parties. Nowadays, APIs are widely used by big-tech companies (e.g., Uber uses Google Maps' API to locate you and your driver) and gaining popularity in the banking industry (e.g., Zelle allows depositors in the U.S. to transfer money among their bank accounts within minutes via API).[39]

Open Banking: Fintech and Banking Disruption There are many players in the nascent industry of open banking, 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 to support traditional banks. In the second segment, financial data aggregation companies (e.g., Mint) partner with financial institutions to get access to traditional banks' financial data via APIs, so that consumers can manage their personal finances from a single dashboard. Taking one step beyond "information aggregators," the third segment—called "lending marketplaces" with Funding Xchange as a leading example—aims to provide a platform where borrowers and lenders exchange information for more efficient loan/financing decisions.

While incumbent banks still hold the keys to the vault in terms of rich transaction data as well as trusted client relationships, they often view the opening of these data as more of a threat than an

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[39]For more discussions on API and its legal issues, see "Open Banking, APIs, and Liability Issues" by Rich Zukowsky (2019).

opportunity.[40] This is especially true for fintech challengers who offer competing services and have gained valuable new (e.g., alternative unstructured) data via their modern customer relationships, an aspect that is highlighted by our paper.

Open Banking: Recent Growth and Development outside Europe 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 in 2020. Allied Market Research reports that the open banking market, accelerated by the pandemic, has become part of the ongoing disruption in the financial sector and will grow at 24.4% annually during the period of 2021-2026. According to the OBIE's latest annual report, over 3 million customers have connected their accounts to trusted third parties by February 2021, up from 1 million in January 2020. In another related report that focuses on how small businesses in the U.K., the OBIE together with Ipsos MORI found that 50% of surveyed small businesses now use open banking providers as of December 2020. What is more, 18% of surveyed small businesses took alternative credit (i.e., not from traditional bank), and "*open banking data is increasingly being used to offer credit as it allows lending providers to more accurately assess creditworthy borrowers and shape funding solutions specific to their needs.*"

Open banking is no longer just a European initiative, as more and more areas are becoming open banking friendly. Hong Kong has already developed its own open banking regulation "Open API" in 2018. Since February 2021, Brazilian Central Bank has launched the Open Banking system that facilitates sharing of data, information and financial services by bank customers across technology platforms, under customers' authorization.

In contrast, countries like U.S. and China are taking the free market approach regarding the open banking ecosystems. In the U.S., for decades traditional banks have used credit reports as the main tools to determine who gets a loan. However, credit reports generally reflect a person's borrowing history, leaving customers with only cash or debit cards unserved. Besides the product "UltraFICO" jointly launched by FICO, Experian, and Finicity mentioned in introduction, a recent WSJ article reports that JPMorgan, Bank of America and other big banks have been using their own customers' bank-account activities to approve financing for applicants with limited credit histories. A natural question is: why can't JPMorgan approve a credit-card application from a borrower who has a deposit account at Wells Fargo, if this borrower agrees? Indeed, this WSJ article reported that "*About 10 banks agreed to exchange data, (which is) an unusual level of collaboration.*" This is essentially open banking.[41]

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[40]Major traditional banks are 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.

[41]This plans grew out of Project REACh (Roundtable for Economic Access and Change), now an effort

C Online Appendix

C.1 Proof of Lemma 2

In this proof, denote by p_{ij} the probability that the bank observes signal i and the fintech observes signal j, regardless of which lender has a better screening ability. This is slightly different from its definition in the baseline case in Section 3, but it is more convenient to use in this extension. To be consistent, let

$$\phi(r, x_f) \equiv \frac{p_{LH}}{p_{HH}[\mu_{HH}(1+r) - 1]} = \frac{x_b(1 - x_f)}{\tau r - (1 - x_b)(1 - x_f)},$$

regardless of which lender has a better screening ability. Throughout this proof, we highlight the argument x_f in $\phi(r, x_f)$ since Lemma 2 is about the property of V_h as function of x_f; and it is easy to see that $\phi(r, x_f)$ decreases in x_f.

Given $\xi \in (0, 1)$, recall that we implicitly define a threshold $\hat{x}_f(\xi)$ based on the equality in (16), i.e., $\hat{x}_f(\xi)$ is the unique solution to the following equation (with x_f being the argument; note that RHS decreases while LHS increases in x_f)

$$\frac{1 - \xi}{1 - \xi\phi(\overline{r}, x_f)} = \frac{x_f(1 - x_b)}{x_b(1 - x_f)}.$$

Such solution $\hat{x}_f(\xi) \in (0, 1)$ always exists for any $\xi \in (0, 1)$ as the RHS ranges from 0 to ∞ when x_f goes from 0 to 1, while the LHS takes a value between zero and one.

We also define $\tilde{x}_f(\xi)$ as the solution to the following equation

$$\xi = 1 - \frac{p_{HL}}{p_{LH}}\phi(\overline{r}, x_f) = 1 - \underbrace{\frac{x_f(1 - x_b)}{\tau\overline{r} - (1 - x_b)(1 - x_f)}}_{\equiv \Phi(\overline{r}, x_f)}. \tag{28}$$

One can easily show that $\Phi(\overline{r}, x_f)$ is increasing in x_f given $\tau\overline{r} - 1 + x_b > 0$ which holds under condition (1), so $\tilde{x}_f(\xi)$ is uniquely defined. And, $\Phi(\overline{r}, x_f = 0) = 0$ implies that $\tilde{x}_f(\xi) > 0$, but it is possible that $\tilde{x}_f(\xi) > 1$.

Scenario 1. Suppose that $\tilde{x}_f(\xi) \leq 1$. Since $\hat{x}_f(\xi) \in (0, 1)$, we can define

$$\hat{\hat{x}}_f(\xi) \equiv \max(\hat{x}_f(\xi), \tilde{x}_f(\xi)) \leq 1,$$

which implies the following result that will be useful in our later proof:

$$\xi > 1 - \frac{p_{HL}}{p_{LH}}\phi(\overline{r}, x_f) \text{ for } x_f > \hat{\hat{x}}_f(\xi). \tag{29}$$

launched by the Office of the Comptroller of the Currency. For details, see this WSJ report.

We now prove our claim in Lemma 2. There are potentially three cases to consider, and from now on we denote $\hat{x}_f(\xi)$ and $\hat{\hat{x}}_f(\xi)$ by $\hat{x}_f$ and $\hat{\hat{x}}_f$ for simplicity.

Case 1. $x_f \in [0, \hat{x}_f)$. From the indifference conditions (14) and (15), it is ready to derive

$$m_f = \frac{1 - \phi(\overline{r}, x_f)}{1 - \xi\phi(\overline{r}, x_f)},$$

which increases in ξ as claimed in the main text. We also have $\underline{r} = \frac{1-x_f}{\tau}$ and

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

Both are the same as in the baseline model with $\xi = 0$. That is, the fintech affinity only affects the probability that the fintech will make an offer upon seeing a good signal, but does not affects its interest rate distribution. We also have

$$\overline{F}_b(r) = \frac{\phi(r, x_f) - \xi}{1 - \xi},$$

which has a mass point at the top with a size of $\lambda_b = \frac{\phi(\overline{r}, x_f) - \xi}{1-\xi}$. It is clear that the bank sets a lower interest rate in the sense of FOSD when ξ is higher. This because when the fintech makes offer more frequently, the bank has to compete more fiercely.

The expected payment of a high-type borrower is

$$(1 - m_f)\mathbb{E}[r_b] + m_f[\xi\mathbb{E}[r_f] + (1 - \xi)\mathbb{E}[\min\{r_f, r_b\}]].$$

Here the only difference, compared to the baseline model, is that when the fintech also makes an offer, there is a chance of ξ that the borrower only takes the fintech's offer. Using the fact that

$$\mathbb{E}[r_f] + (1 - \xi)\mathbb{E}[\min\{r_f, r_b\}] = \underline{r} + \int_{\underline{r}}^{\overline{r}} \overline{F}_f(r)\phi(r, x_f)dr,$$

we can derive that the above expected payment equals

$$\underline{r} + (\overline{r} - \underline{r})\phi(\overline{r}, x_f)\frac{1 - \xi}{1 - \xi\phi(\overline{r}, x_f)}.$$

Then we have

$$V_h(x_f; \xi) = (\overline{r} - \underline{r})\frac{1 - \phi(\overline{r}, x_f)}{1 - \xi\phi(\overline{r}, x_f)}.$$

Since both $\underline{r}$ and $\phi(\overline{r}, x_f)$ decrease in x_f, V_h increases in x_f. It is also clear that V_h increases in ξ given $\underline{r}$ is independent of ξ, and so $V_h(x_f; \xi) > V_h(x_f; 0)$.

Case 2. $x_f \in \left[\hat{x}_f, \hat{\hat{x}}_f\right]$. (If $\hat{x}_f = \hat{\hat{x}}_f$ which holds when $\hat{x}_f \geq \tilde{x}_f$, this case is empty and we directly jump to Case 3.) This case holds when $\hat{x}_f < \tilde{x}_f$ so that $\hat{x}_f < \hat{\hat{x}}_f$, and for $x_f \in \left[\hat{x}_f, \hat{\hat{x}}_f\right]$ we have

$$\frac{1 - \xi}{1 - \xi \phi(\overline{r}, x_f)} \leq \frac{p_{HL}}{p_{LH}} \tag{30}$$

and

$$\xi \leq 1 - \frac{p_{HL}}{p_{LH}} \phi(\overline{r}, x_f). \tag{31}$$

The key condition (31) follows from the definition of $\tilde{x}_f(\xi)$ in (28).

We construct the following equilibrium with $\pi_b = 0 < \pi_f$. The indifference conditions are:

$$p_{HH}(1 - \xi)\overline{F}_f(r)[\mu_{HH}(1 + r) - 1] - p_{HL} = 0,$$

and

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

When the fintech makes an offer, it competes with the bank only when the bank also makes an offer (which happens with probability m_b) and the borrower is not hit by the preference shock (which happens with probability $1 - \xi$); otherwise, it is the monopoly lender. Then it is straightforward to derive

$$\phi(\underline{r}, x_f) = (1 - \xi)\frac{p_{LH}}{p_{HL}} \tag{32}$$

and $\pi_f = \frac{p_{HL}}{1 - \xi} - p_{LH}$, which must be positive under (30). The fintech's interest distribution is

$$\overline{F}_f(r) = \frac{\phi(r, x_f)}{\phi(\underline{r}, x_f)},$$

and it has a mass point at the top with a size of $\lambda_f = \frac{p_{HL}}{p_{LH}} \frac{\phi(\overline{r}, x_f)}{1 - \xi}$. And, the bank makes an offer, upon seeing a good signal, with probability m_b which solves

$$\xi + (1 - \xi)(1 - m_b) = \frac{\phi(\overline{r}, x_f)}{\phi(\underline{r}, x_f)},$$

with bank's interest rate distribution being $\overline{F}_b(r) = \frac{\phi(r, x_f) - \phi(\overline{r}, x_f)}{\phi(\underline{r}, x_f) - \phi(\overline{r}, x_f)}$. This is well-defined if $\frac{\phi(\overline{r}, x_f)}{\phi(\underline{r}, x_f)} \leq 1$.

But under condition (31), we can show that $\underline{r} < \overline{r}$ hence $m_b < 1$, and $\lambda_f = \frac{p_{HL}}{p_{LH}} \frac{\phi(\overline{r}, x_f)}{1 - \xi} \in (0, 1)$; therefore the constructed equilibrium bank strategy is well-defined. To show this, it suffices to ensure that in Eq. (32), we have

$$\phi(\underline{r}, x_f) = (1 - \xi)\frac{p_{LH}}{p_{HL}} \geq \phi(r, x_f) \geq \phi(\overline{r}, x_f) = \frac{p_{LH}}{p_{HH}[\mu_{HH}(1 + \overline{r}) - 1]}.$$

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This requires that $1 - \xi \geq \frac{p_{HL}}{p_{HH}[\mu_{HH}(1+\overline{r})-1]}$ which is equivalent to

$$\xi \leq 1 - \frac{p_{HL}}{p_{LH}}\frac{p_{LH}}{p_{HH}[\mu_{HH}(1+\overline{r})-1]} = 1 - \frac{p_{HL}}{p_{LH}}\phi(\overline{r}, x_f).$$

This is exactly the condition in (31), which also ensures $\lambda_f = \frac{p_{HL}}{p_{LH}}\frac{\phi(\overline{r},x_f)}{1-\xi} \in (0,1)$. Under this equilibrium, the expected payment of the high-type is

$$[\xi + (1-\xi)(1-m_b)]\mathbb{E}[r_f] + (1-\xi)m_b\mathbb{E}[\min\{r_f, r_b\}]$$
$$= \underline{r} + \int_{\underline{r}}^{\overline{r}} \overline{F}_f(r)[1 - (1-\xi)m_b + (1-\xi)m_b\overline{F}_b(r)]dr$$
$$= \underline{r} + \int_{\underline{r}}^{\overline{r}} \left(\frac{\phi(r, x_f)}{\phi(\underline{r}, x_f)}\right)^2 dr,$$

where the second equality used the fact the square-bracket term equals $\frac{\phi(r,x_f)}{\phi(\underline{r},x_f)}$, which is from the fintech's indifference condition. Then we have the high-type's value to be

$$V_h = \int_{\underline{r}}^{\overline{r}} \left(1 - \left(\frac{\phi(r, x_f)}{\phi(\underline{r}, x_f)}\right)^2\right) dr.$$

Notice that $\underline{r}$ solves $\phi(\underline{r}, x_f) = (1-\xi)\frac{x_b(1-x_f)}{x_f(1-x_b)}$ and $\phi(r, x_f)$ is a decreasing function in r. It is then easy to see that $\underline{r}$ increases in both x_f and ξ. On the other hand, we have

$$\frac{\phi(r, x_f)}{\phi(\underline{r}, x_f)} = \frac{\frac{\tau}{1-x_f}r - 1 + x_b}{\frac{\tau}{1-x_f}\underline{r} - 1 + x_b}.$$

Given $\underline{r}$ increases in x_f, one can check that this expression increases in x_f; given $\underline{r}$ increases in ξ, this expression also increases in ξ. Therefore, V_h decreases in both x_f and ξ.

Case 3. When $x_f \in \left(\hat{x}_f, 1\right]$, we have (31) fails, so that the bank exits, i.e., $m_b = 0$, given the argument in Case 2. As a result, the fintech will charge the monopoly interest rate $\overline{r}$ and the equilibrium $V_h(x_f; \xi) = 0$, which is weakly decreasing in x_f. And, since $V_h(x_f; 0) > 0$ for all x_f in the baseline as shown in Eq. (18), we have the desired claim $V_h(x_f; \xi) < V_h(x_f; 0)$.

Scenario 2. Suppose that $\tilde{x}_f > 1$. Then, $\hat{\tilde{x}}_f \equiv \max(\hat{x}_f, \tilde{x}_f) > 1$. Therefore Case 1 remains unchanged, while for Case 2 we have $x_f \in [\hat{x}_f, 1]$, and Case 3 is void. All the proofs in Scenario 1 go through. Q.E.D.

C.2 Two Fintech Lenders

C.2.1 Asymmetric Fintechs

Lemma 5. *Suppose that there are lenders with asymmetric screening abilities $x_s > x_m > x_w$ (subscripts denote the strong, medium, and weak lender respectively), then there are only two active lenders.*

Proof. Lender profit (as evaluated at the lowest interest rate $\underline{r}$) is[42]

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

Hence,

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

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

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

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

C.2.2 Symmetric Fintechs

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

$$x'_f > x_b > x_f.$$

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

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

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

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

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

$$x_f \nearrow x_b \nearrow x_{f'} \equiv x. \tag{33}$$

---

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

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

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

$$\pi_b(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right]^2}_{\text{winning both competitors}} [\mu_{HHH}(1+r) - 1] \tag{34}$$

$$- 2 \underbrace{p_{HHL}}_{b \text{ and one } f \text{ make mistakes}} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right]}_{\text{bank wins over competing } f} - p_{HLL} \tag{35}$$

Fintech's indifference condition

$$\pi_f(r) = p_{HHH} \underbrace{\left[1 - m_f + m_f \overline{F}_f(r)\right] \overline{F}_b(r)}_{\text{winning both competitors}} [\mu_{HHH}(1+r) - 1] \tag{36}$$

$$- \underbrace{p_{LHH}\left[1 - m_f + m_f \overline{F}_f(r)\right] - p_{HHL}\overline{F}_b(r)}_{\text{fintech and its one competitor make mistake}} - p_{LHL}. \tag{37}$$

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

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

Accordingly, the bank's profit is given by

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

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

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

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

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

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

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

After mandatory open banking, there are three equilibria, but borrower surplus are equivalent when $\delta \to 0$.[43] For the calculation, we use the asymmetric equilibrium. Let m' denote the probability that fintech makes an offer after mandatory open banking, then

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

Under the parameter setting (33), h-type surplus depends on the relative relationship between m' and $m_f(2 - m_f + x m_f)$.

The bank's profits before open banking and the fintechs' profits after open banking show the following relationships between m_f, m', and x:

$$
\begin{aligned}
\pi_b &= p_{HHH}(1 - m_f)^2\left[\mu_{HHH}(1+\bar{r}) - 1\right] - 2p_{HHL}(1 - m_f) - p_{HLL} \to 0 \\
&\Rightarrow (1 - m_f)^2 \frac{\bar{r}}{\underline{r}} - 1 + (1 - x)\,m_f(2 - m_f + m_f x) \to 0;
\end{aligned} \tag{38}
$$

---

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

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

but avoids loss from l type

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

In equilibrium these two effects cancel out exactly

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

$$\pi_f = p_{HH} \left(1 - m'\right) \left[\mu_{HH} \left(1 + \bar{r}\right) - 1\right] - p_{HL} = 0$$

$$\Rightarrow \left(1 - m'\right) \frac{\bar{r}}{\underline{r}} - 1 + m' \left(1 - x\right) = 0. \tag{39}$$

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

$$\underbrace{\left(1 - m_f\right)^2 \left[\frac{\bar{r}}{\underline{r}} - \left(1 - x\right)\right] - x + m_f^2 x \left(1 - x\right)}_{LHS \text{ from } (38)} \to \underbrace{\left(1 - m'\right) \left[\frac{\bar{r}}{\underline{r}} - \left(1 - x\right)\right] - x = 0,}_{LHS \text{ from } (39)}$$

which implies

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

Plug this back into (38) and (39), we have

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

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