The Welfare Effects of Open Banking Data Versus Collateral

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Abstract

Open banking can alter the information structure of credit markets by furnishing fintechs with more financial data on their customers and hence enhancing their screening capabilities. We investigate the welfare implications of open banking by constructing a model of a loan market with adverse selection. In this market, a fintech, reliant on information technology to assess borrowers' credibility, competes with a traditional bank that employs collateral to differentiate between various borrower types. We find that enhancing the fintech's monitoring capacity through the provision of free access to borrowers' information may not necessarily lead to improved welfare. This suggests that complete data sharing (i.e., granting the fintech full access to borrowers' data) is not always the optimal solution and could potentially reduce welfare. Specifically, when the bank is sufficiently proficient in utilizing collateral, partial data sharing might be the preferred option.

KEYWORDS: Open Banking, Optimal Data Sharing, Loan Market Competition, Digital Economy

JEL CLASSIFICATION: D82, L13, G21, G23

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1 Introduction

The ubiquity of personal data has brought about radical changes in how markets function. Legislation such as the GDPR[1] and the CCPA[2] has been established to safeguard the collection and processing of data by ensuring ownership of information generated through consumers' digital interactions is returned to the consumers themselves. This reassertion of ownership paves the way for innovative and welfare-improving applications of this data.

More closely related to financial markets, customer data have enabled banks to create new financial products and transform the way traditional banking activities are conducted. The adoption of the *(Revised) Payment Services Directive* (known as PSD2)[3] provides the legal framework governing data ownership and sharing within the European Union. PSD2 requires European banks to offer automated access to customer transaction accounts for qualified third parties, given the customers' consent, through API technology.[4] This initiative, known as *open banking*, aims primarily to "support innovation and competition in retail payments and enhance the security of payment transactions and the protection of consumer data."

Data are particularly valuable to new "financial technology companies" (fintechs) that leverage technology to offer a wide range of financial services, including but not limited to banking, payment processing, investment management, and insurance services.[5]. Consequently, open banking has the potential to transform financial markets by enabling new entrants such as fintechs to compete with traditional financial intermediaries in providing banking products.

One reason data can be particularly valuable to lenders is the observation that financial

[1]The General Data Protection Regulation. See https://gdpr-info.eu/

[2]California Consumer Privacy Act. See https://oag.ca.gov/privacy/ccpa

[3]For further information, see https://www.ecb.europa.eu/paym/intro/mip-online/2018/html/1803˙revisedpsd.en.html

[4]This access includes both retail and corporate customers. The APIs facilitate the synchronization, linking, and connection of databases. Within the banking system, these APIs establish connections between a bank's database (which contains customer information) and various applications or programs, thus creating a network that supports the promotion of services, payments, and products tailored to individual customers. For further information, see Giorgio et al. (2018), pages 43 to 46.

[5]For further discussion on the definition and evolution of fintechs, see Giglio et al. (2021)

markets suffer from information asymmetries. In situations of asymmetric information, it is well understood that the creation and dissemination of information (in the form of data) can mitigate potential misallocations and inefficiencies. Nevertheless, since open banking allows fintechs access to customers' financial data, enhancing their competitive position, it possesses the potential to redistribute market power and thus alter the nature of financial products available in the market. Consequently, the possibility of data sharing raises several economically significant questions. For example, does open banking increase competition among lenders? If so, does it advantage borrowers or enhance market efficiency?[6]

To address these questions, we examine a model of a credit market characterized by asymmetric information between lenders and borrowers. In particular, we consider an economy populated by financially constrained entrepreneurs, a traditional bank, and a fintech company. Entrepreneurs are endowed with risky projects that require a fixed capital investment to start off. The potential return of each project varies, with entrepreneurs being differentiated based on the probability of generating a positive return. We categorize entrepreneurs into two types: low and high, where only the high-type entrepreneurs possess projects deemed creditworthy. Additionally, entrepreneurs have a fixed quantity of a physical asset at their disposal, which can serve as collateral should they opt for a loan.

As in Bester (1985), borrowers with a lower probability of repayment are less inclined to accept collateralized loans than those with a higher likelihood of repayment. Consequently, a potential lender can effectively screen borrowers based on their repayment probabilities by offering loan agreements with appropriate collateral requirements. However, we make the conventional assumption that collateralization is costly and incurs a deadweight loss. As in Boot, Thakor, and Udell (1991), we assume that, because of the transaction costs in collateralization and also because the borrowers' assets might be components of a productive plan that the lenders can not practice, the collateralized assets of the borrowers are worth more to the borrowers than to the lenders. A pivotal assumption

[6]Regarding the relationship between regulatory regimes and the rise of fintech lending activities, see Greck et al. (2018)

in our model is that the bank holds a comparative advantage over the fintech in leveraging collateral as a means of securing loans.[7] This advantage stems from the banks' established expertise and is corroborated by empirical evidence.[8] Consequently, this implies that the deadweight loss associated with transferring a collateralized asset to a bank is lower than transferring it to a fintech.

Another important component of our model, is that the bank has access to a dataset from previous transactions, which can be used to partially identify the type of entrepreneur applying for a loan. Nonetheless, we posit that there is a distinct difference in the ability of the two lenders to analyze this data. Specifically, we assume that the fintech is more capable than the bank at utilizing data. This implies that, given access to the same data, a fintech can better than the bank identify, albeit imprecisely, the type of a potential borrower. Hence, we model asymmetric competition between a data-driven lender (the fintech) and a collateral-dependent lender (the bank).

In our setting, the two lenders compete by offering (potentially collateralized) debt contracts. Given their asymmetry in data utilization and collateral leverage, their competition in loan contracts leads to an equilibrium in mixed strategies, where each asymmetry can solely cause the non-existence of pure Nash equilibrium. Firstly, the competition in collateralized loans when lenders have different cost of collateral is reminiscent of a Bertrand price game in continuous space with different marginal costs. While such game does not have a pure Nash equilibrium under the conventional rationing rule, the mixed strategy equilibrium can be analyzed using a methodology similar to that described in Blume (2003). Moreover, the difference in lenders' ability in identifying borrowers' type based on data forms an equilibrium structure similar to the model of sales proposed by Varian (1980). In Varian (1980), there are two sellers who cater to two distinct groups of buyers: *informed* buyers, who receive offers from both sellers and choose the one with the lower price, and *uninformed* buyers, who purchase from only one seller regardless of

[7] In an early contribution, Manove, Padilla, and Pagano (2001) highlights the inherent preference of banks in collateralized loans.

[8] For instance, to examine whether banks have an advantage over other lenders in utilizing collateral, Cerqueiro, Ongena, and Roszbach (2020) studied an exogenous transfer of priority rights from banks to other creditors and found that this affects future corporate financing. Gambacorta et al. (2022) and Gopal and Schnabl (2022) highlight the comparatively infrequent use of collateral by fintechs relative to traditional banks.

the price. In our model, borrowers identified by the fintech as good risks (akin to Varian's "informed customers") receive loan offers from both lenders, whereas those not identified as good risks by the fintech (akin to Varian's "uninformed customers") can only obtain a loan offer from the bank. Thus, our model can be viewed as an asymmetric adaptation of Varian's model, with the crucial distinction being that only the bank deals with uninformed customers.

In our model, open banking is conceptualized as the transfer of data from the bank to the fintech, enhancing the fintech's capability to accurately identify a borrower's type. A critical feature of the equilibrium in our model is that as the precision of the fintech's technology improves, competition with the bank intensifies, compelling the bank to increase its collateral requirements. This escalation in collateral, however, entails a deadweight loss, producing two countervailing effects.

On one hand, a more proficient fintech, capable of effectively identifying credible borrowers, can offer unsecured loans, thereby reducing the deadweight loss associated with collateral. On the other hand, the intensified competition forces the bank to offer more appealing contracts, characterized by lower interest rates and higher collateral levels. This, in turn, may diminish market efficiency. The interplay between these opposing effects leads to situations where open banking could either enhance or undermine social welfare in the loan market.

In short, by investigating the equilibria resulting from the asymmetric competition of a data-driven fintech and a collateral-dependent bank in a loan market with adverse selection, we show that strengthening the fintechs by providing them free access to the borrowers' data is not always welfare improving and might have a negative effect on the efficiency of the market. We provide the condition under which open banking can improve the efficiency of the loan market. Our findings suggest that open banking enhances credit market welfare only if the traditional banks' efficiency in securing loans is sufficiently low or if fintech firms demonstrate strong predictive abilities regarding borrowers' creditworthiness. In other words, we find that in situations where the cost of collateral for the bank is sufficiently high, the market efficiency in the equilibrium improves by increasing the strength of fintech through provision of free access to borrowers'

data. However, we find a non-monotone relation between the market efficiency and the fintech's monitoring strength in the equilibrium when the cost of collateral for the bank is low. In these cases, the competition with a stronger fintech lowers the efficiency of bank's contracts which can potentially offset the benefits of the provision of unsecured loans by the fintech, specifically if fintech's monitoring precision after having access to data is not sufficiently high.

Moreover, in situations of non-monotone relation between market efficiency and fintech's strength, we find that providing borrowers with ownership of their own data might not be the optimal open banking regime. Indeed, we show that market efficiency can be improved in such cases by restraining the flow of data to fintechs to a certain optimal level. Hence, we emphasize on the importance of designing an optimal information structure in loan markets. Our analysis enables policy makers to anticipate the impact of open banking on credit market efficiency and design an optimal data sharing regime by evaluating the strength of traditional banks and fintech firms in utilizing collateral and data to mitigate adverse selection. In situations where traditional banks efficiently provide secured loans and the negative effects of intensified competition from a strong fintech on market efficiency may outweigh the welfare benefits of transitioning to unsecured loans, implementing a partial data sharing regime would be prudent, limiting fintech firms' access to borrower data to levels that optimize the market efficiency.

Related Work The literature on fintechs' challenging the banking sector is growing fast. Berg, Fuster, and Puri (2022) present a valuable literature review on the activities undertaken by fintechs. Giglio et al. (2021) also provide a comprehensive study of the emergence of fintechs in the past decades. In what follows, we mention a few recent and closely related articles.

The most related work to our paper is He, Huang, and Zhou (2023) that models competition between a bank and a fintech that rely on monitoring borrowers in a loan market with adverse selection. Nonetheless, and in sharp contrast to our paper, these authors do not allow for any screening device (such as collateral). He, Huang, and Zhou (2023) demonstrate that open banking can harm borrowers' surplus by over-empowering the

fintech, even when the borrowers own the right to share their financial data. However, in their model, whenever open banking harms the borrowers, it increases the market efficiency. Our paper complements their result in the sense that we provide the condition under which open banking can deteriorate the market efficiency while increasing borrowers' surplus in presence of a screening device.

Another closely related work that studies the consequences of an open banking regime is Parlour, Rajan, and Zhu (2022) that models the competition between a fintech that provides payment services with a bank that competes in the payment services but is a monopolist in the lending market. They show that the competition from the fintech can have an ambiguous effect on the loan market since it can harm the information spillover from the payment services activities of the bank that are useful in credibility assessment of the borrowers. Our results show that even if fintechs compete in the credit market, the effect of providing them with free access to borrowers' data in the open banking regime remains ambiguous.

Our paper contributes to the growing literature on the study of fintechs' business model and the effects of fintech entry in the credit market. Ghosh, Vallee, and Yao (2021) present the theoretical and empirical evidence for the synergy between fintech' cashless payments and their lending activities. Their results confirms the assumption of our model that the eminence of cashless payments can enhance the efficiency of fintechs screening in the loan market. Yannelis and Zhang (2021) study the effect of increased competition in the lending market when acquiring screening technology has a fixed cost. They provide the empirical evidence confirming their theoretical result that predicts the intensified competition in the lending market can increase the interest rates of the loans through decreasing the incentives of the lenders to invest in the fixed-cost screening technology. Vives and zhiqiang (2023) provide a spatial model of loan markets to study the effect of information technology on competition and stability of lenders, investment, and welfare. They show that while an IT improvement incentivizes investment, its effect on the competition, stability, and welfare depends essentially on whether IT weakens the influence of lender–borrower distance on monitoring costs. While our results is aligned with their insight about the potential adverse effects of intensified competition in the credit mar-

ket, our model differs mainly by considering the technological differences of banks and fintechs in mitigating the credit market inefficiencies due to adverse selection.

A main feature of our model is the avails of collateral and data in the credit market. Jing (2021) explores the same idea of fintechs utilizing information technology to assess borrowers credibility, in contrast with traditional banks that depend on collateral. Their main result shows that the competition with different technologies result in coarse information acquisition by fintechs, where the fintechs only acquire single-threshold structure to screen out borrowers below the threshold, despite having the potential to secretly acquire more information to offer tailored loans to steal the bank's customers. Serfes, Wu, and Avramidis (2023) also explore the differences of the banks and fintechs lending in using collateral, emphasizing on fintechs proficiency in short-term lending in contrast with banks expertise in long -term lending. They provide theoretical ground for substitutability of collateral and data. While these papers investigate the role of collateral in the competition of banks and fintechs in the credit market, they ignore the signaling role of collateral as a mean for self-selection. In our model, collateral is seen not merely as an alternative mode of repayment, but a potential device for borrowers to signal their creditworthiness.

Xu et al. (2022) empirically investigates the relationship between fintechs' activities and provision of bank loans. They show that while fintechs increase firm access to bank loans, their activities positively contribute to unsecured loans without collateral and longer maturity. Also, Gambacorta et al. (2022) provide empirical evidence that the rise of data-driven credibility monitoring can reduce the role of collateral in the loan markets, while making the loans more sensitive to the business activities of the firms. Our model rationalizes these observations in the context of the competition between a data-driven and collateral-dependent lender.

2 Model

There is a single good with a unit price in terms of dollars, spanning two time periods: today and tomorrow.[9] For simplicity, the net risk-free interest rate between these two periods is normalized to zero. Furthermore, we assume that all agents in our economy are risk-neutral and do not discount the future, meaning they are indifferent to consuming one unit of the good in either period.

Borrowers. There is a continuum of borrowers of measure one. Borrowers possess no cash at present but are all endowed with physical assets that can serve as collateral.[10] The value of these assets for any borrower is C (uniform across all borrowers), and we assume this is adequate for effective signaling (refer to Assumption 3 for more details). Additionally, each borrower has a project requiring 1 dollar to initiate today and yields a random return $\tilde{Y}$ (in dollars) tomorrow.

There are two types of borrowers: good types ($i = g$) and bad types ($i = b$). The share of type i borrowers in the population is λ_i, where $\lambda_g \equiv \lambda$ and $\lambda_b \equiv 1 - \lambda$. The borrower's type ($i$) is her private information. The return of the borrower's project depends on her type. In particular, a project returns $\tilde{Y} = Y$ with probability θ_i, or $\tilde{Y} = 0$ with probability $1 - \theta_i$, where $\Delta\theta \equiv \theta_g - \theta_b > 0$.

We assume that while good types possess projects with a strictly positive net present value (NPV), bad types have projects with a strictly negative NPV. [11] Moreover, we posit that the average project in the population has a strictly negative NPV. Let $\bar{\theta} \equiv \lambda\theta_g + (1 - \lambda)\theta_b$. Under this setting, we introduce the following assumption:

$$\bar{\theta}Y < 1 < \theta_g Y \tag{1}$$

This assumption implies that, under asymmetric information, extending a loan indiscriminately, without additional evidence, would result in an unprofitable outcome for the

[9] Given the good's unit price, we will interchangeably refer to the good and dollars as representing the same value.

[10] The assumption of no cash availability today is for simplicity and without loss of generality. We could alternatively allow borrowers to have wealth $W < 1$ and the results would still hold.

[11] The latter assumption is merely for simplification. All results hold as long as $\theta_b < \theta_g$.

lender.[12]

Lenders. In the economy, there are two types of lenders: a traditional bank (he) and a potential entrant fintech company (she): $l = \{bank, fin\}$. Each lender can raise funds inelastically at a zero interest rate, which reflects the economy's risk-free rate, and can provide one-dollar loans to borrowers. These loans are structured as secured debt. Specifically, a loan contract is represented by a pair (ρ, c), where ρ is the repayment amount (principal plus interest) a borrower owes to a lender, and c is the amount of collateral that the lender will seize in case of borrower default. We assume that the success state of the project is observable and verifiable by the lenders. This implies that borrowers can not strategically default when the project is successful and $\rho > c$.

Consistent with the assumptions in Bester (1987), we posit that collateralizing assets incurs costs. However, in our model, it is the lenders who bear the cost of collateralization. Specifically, in the event of a default, a lender captures less than the true value of the collateral, potentially due to transaction costs or other inefficiencies involved in transferring the collateral from the borrower to the lender and constitutes an implicit social cost.[13]

A key assumption in our analysis is that the cost of collateralization for fintechs is higher than for banks. This can be justified by positing that banks, owing to their size and experience, have more efficient divisions managing foreclosures. Additionally, the lower collateralization cost for banks may be viewed as an advantage in lending to local businesses, with whom they often have established relationships. As highlighted in the introduction, this assumption is supported by empirical evidence. For example, Cerqueiro, Ongena, and Roszbach (2020) demonstrate the collateralization advantage of banks compared to other creditors. Furthermore, studies such as Gambacorta et al. (2022) and Gopal and Schnabl (2022) underscore the infrequency with which fintechs utilize col-

[12]This assumption is sufficient but not necessary. In the next section, we introduce the sufficient condition for the existence of a separating signaling equilibrium.

[13]There are several practical instances supporting this assumption. For example, consider a house as collateral. After foreclosure, a lender often incurs a significant loss in the house's value upon taking possession. Similarly, for a physical asset like a factory belonging to an established firm, the value can diminish considerably in foreclosure, either because the borrower has specialized knowledge in its utilization or due to unique applications of the asset that only the borrower can execute.

lateral in their loans. Let the value of one unit of collateral for lender l be denoted as γ^l. Based on the preceding discussion, we impose the following assumption:

$$0 = \gamma^{fin} < \gamma^{bank} \equiv \gamma < 1. \tag{2}$$

The assumption that $\gamma^{fin} = 0$ is to simplify the analysis. Indeed, assuming that $0 < \gamma^{fin} < \gamma^{bank}$ does not alter our results.

We previously argued that good types have enough collateral to effectively signal their type. The necessary and sufficient condition for this can be represented as follows:

$$C > \frac{\theta_g - \theta_b}{\theta_g(1-\theta_b) - \theta_b(1-\theta_g)\gamma^B} \tag{3}$$

To simplify our notation, we will focus on contracts where $c \leq C$. This implies that the amount of collateral specified in the loan contract is less than or equal to the total collateral available to the borrower.

Suppose lender l signs a loan contract (ρ, c) with type i. Then type i earns payoff:

$$U_i(\rho, c) = \theta_i(Y - \rho) - (1 - \theta_i)c + C, \tag{4}$$

whereas lender l earns profit:

$$\pi_i^l(\rho, c) = \theta_i\rho + (1 - \theta_i)\gamma^l c - 1. \tag{5}$$

We assume that borrowers accept loan contracts with strictly positive expected payoff, and they choose randomly when being indifferent between two loan contracts.[14]

The Information. Before Open Banking, the fintech has access to some publicly available data, including information shared on social networks, cookies, and other publicly accessible data. In contrast, the bank has access to more comprehensive financial data such as a borrower's wealth, belongings, financial history, and digital footprints. Also,

[14]The competition between lenders with different cost of collateral have characteristics similar to a Bertrand price competition with asymmetric marginal costs. We follow the method of Blume (2003) to find the mixed-strategy equilibria of such games under the conventional rationing rule. We could replace this mixed strategy equilibria with a pay-off equivalent pure strategy equilibrium by assuming that, when indifferent between two loan contracts, borrowers choose the bank contract.

the bank might have confidential data on certain borrowers through previous lending relationships. After open banking, the fintech can have access to some of the data that is traditionally held by the banks.

This data is useful in partially identifying a borrower's type. For instance, personal data can provide insights into a borrower's lifestyle and associated riskiness, while financial data can offer more precise information about their creditworthiness. Consistent with related theoretical works such as He, Huang, and Zhou (2023), we assume that lenders receive independent signals about the repayment probability of each borrower.

Specifically, we assume that for a good-type borrower, the lenders receive independent fully revealing signals with probability $\sigma^l \in [0, 1]$.[15] The more data input into the lenders' algorithms, or the more information available through previous lending relations, the higher σ^l becomes.

According to Giglio et al. (2021), "fintech innovation in lending is found in the use of alternative credit models, online data sources, price risk data analysis, fast lending processes and lower operating costs". Berg et al. (2020) provide evidence that digital footprints of borrowers complement (rather than substitute) traditional credit bureau information. Hence, while lenders' data sets might share some common sources, we posit that the potential differences in lender-specific information and credit scoring methods result in independent signals for lenders. However, our main results can hold as long as lenders' signals are not perfectly correlated.

The game. We model the competition in the loan market as a multi-stage game:[16]

- **Stage One**: Lenders publicly offer loan contracts conditional on the realized signal of the borrowers.
- **Stage Two**: The borrowers privately learn their realized signal at each lender and choose one contract or none.

[15] To clarify, the lender's data processing results in a partially revealing signal $S^l \in \{h, l\}$, with conditional probabilities $\mathbb{P}\{S^l = h|\text{type} = i\} = \sigma_i^l$, where $\sigma_g^l = \sigma^l$ and $\sigma_b^l = 0$. Post-model equilibrium, we discuss the implications of more general signal structures, such as $\sigma_g, \sigma_b \in (0, 1)$.

[16] This game is analogous to one where, in the first stage lenders privately observe signals about each borrower and offer private individual loan contracts, and in the second stage, borrowers choose one or no loan contract.

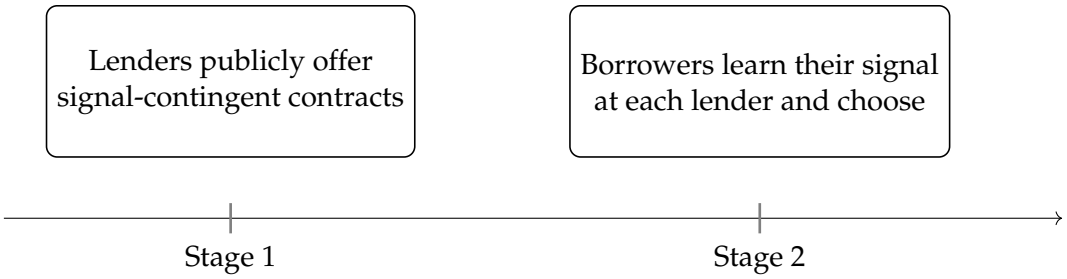

Figure 1: Timing of The Loan Market Competition

In the first stage of the game, the lenders publicly announce the loan contracts that borrowers can receive depending on their realized signal. In the second stage, borrowers apply for loans by providing required information and data to the lenders and learn their signal at each lender. Their signals specify the loan contracts available to them, and they choose either one of the offers or opt for no loan contract.

A crucial assumption in the specification of our model is that, while lenders observe the quality of their rival's signal, they can not observe the realized signal for each borrower. In section 4, we will show that lenders' profits are lower if their signal on each borrower is observable by the other lender. This implies that lenders prefer to keep their signals private, as it is a source of competitive advantage for them.

We characterize the perfect Bayesian equilibrium of the game. An equilibrium consists of a pair of signal-contingent loan offers $A = (a^{bank}, a^{fin})$, the proportions of good-type and bad-type borrowers accepting the loan offers from the bank and the fintech, respectively $D = ((d_g^{bank}, d_b^{bank}), (d_g^{fin}, d_b^{fin}))$, as well as a consistent belief system for the lenders.

3 Equilibrium Characterizations

In this section, we analyze the equilibria of the game. To facilitate understanding, we start with the scenario where data has no value, i.e., $\sigma = 0$. In this case, the bank holds a clear advantage due to its lower cost of collateralizing assets. The bank aims to maximize surplus extraction from borrowers but is constrained by the competitive threat posed by the fintech, similar to the dynamic of a high-cost firm being a competitive threat to a low-cost firm in Blume (2003). Consequently, the equilibrium involves mixed strategies: the bank offers a unique contract to exclude the fintech from the market, while the fintech

randomizes its offers to render the bank indifferent between its unique offer and any contract yielding a higher payoff.[17]

Introducing a strictly positive σ into our model brings about a "*Varian effect*" (Varian, 1980). Specifically, borrowers identified by the fintech as good types (akin to Varian's "informed customers") receive offers from both lenders, while those not recognized as good risks by the fintech (similar to Varian's "uninformed customers") receive offers only from the bank. Thus, a positive σ introduces a significant strategic shift. Considering our assumption that borrowers with a good signal at the fintech are definitively of good type, the fintech in equilibrium does not require collateral from these borrowers. However, those with a bad signal might still be offered a loan with collateral by the fintech. On the other hand, the bank, without extra information, relies on collateral as a self-selection tool. In this scenario, both lenders engage in mixed strategies.

Figure 2 illustrates the (undominated) equilibrium of our game. The bank employs a randomization strategy by offering contracts along the line $U_b = 0$, referred to as the *Incentive Compatibility (IC)* line. On this line, bad-type borrowers are indifferent and consequently do not accept any contracts. The point (ρ^0, c^0) denotes the intersection of the IC line and the fintech's iso-profit line, where the fintech earns zero profit. By offering this contract, the bank eliminates the possibility for the fintech to earn positive profits from any contract on the IC line. Thus, any loan offers by the fintech on the IC line above this point serve merely as a deterrent to prevent the bank from imposing higher terms.[18]

For any positive value of σ, the fintech is able to offer unsecured loans to borrowers with a good signal. As shown in 2, for fintech's offer to be attractive for the good-type borrowers, it should yield a higher utility than the the contract (ρ^0, c^0), which is the most profiting contract that the bank could offer and win all good-type borrowers, if the fintech did not posses an informative signal. Hence, the level of borrowers' utility associated with this contract marks the upper bound of the support for bank' offers, as well as the upper bound for fintech's offers to borrowers with good signal.

[17] Analogous to a simple Bertrand model with asymmetric firms (see Blume, 2003), other equilibria involving dominated strategies could be characterized, leading to reduced social welfare. Hence, we focus on undominated strategy equilibria as detailed in Proposition 1.

[18] The fintech's part of the distribution strategy on this segment of the IC line can take infinite forms. However, as no borrower accepts these offers, it has no impact on the players' payoffs.

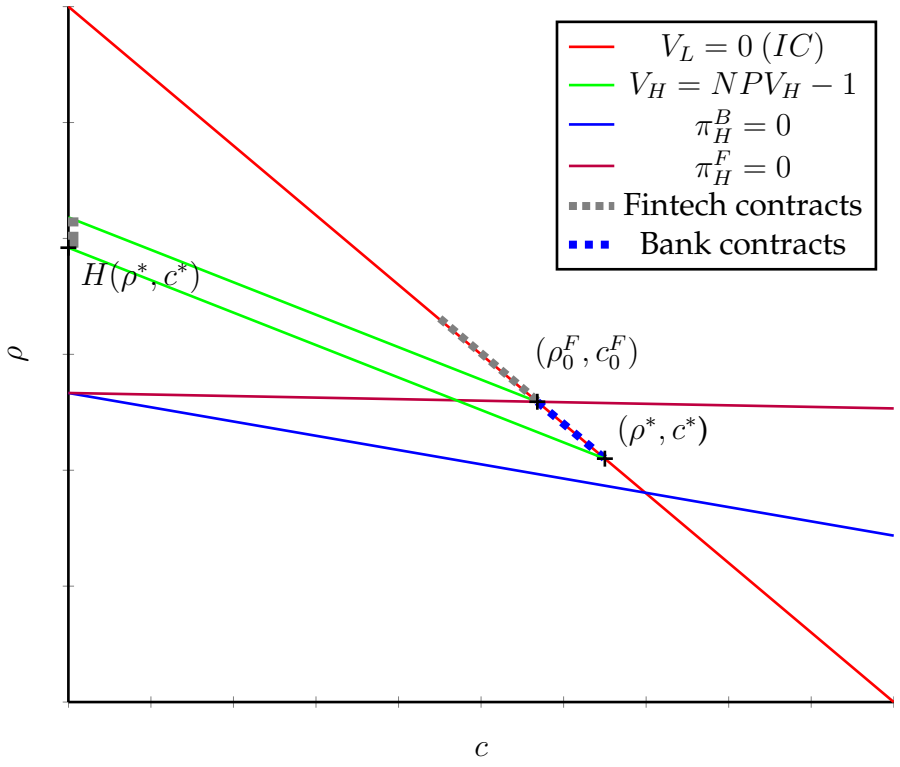

Figure 2: Loan Markets equilibrium

Since fintech's signal is her private information, the bank cannot distinguish between borrowers who have a good or bad signal at the fintech. This result in a trade-off for the bank. Consider the case where fintech offers an attractive unsecured contract to the borrowers with good signal. In one hand, the bank can have the highest profit from borrowers with a bad signal at the fintech (i.e. banks' captive customers) by offering (ρ^0, c^0). This would result in the profit $\lambda(1-\sigma)\pi_g^{bank}(\rho^0, c^0)$, since only the share $(1-\sigma)$ of good-type borrowers who have a bad signal at the fintech accept this offer. On the other hand, to compete with the fintech, the bank can offer more favorable contracts to all borrowers by adjusting its position along the IC line. However, such a contract (ρ^*, c^*) should yield a profit above $(1-\sigma)\pi_g^{bank}(\rho^0, c^0)$ per good-type borrower. If the profit falls below this threshold, the bank would prefer to forfeit the borrowers with a good signal and offer a more profitable contract to the remaining borrowers. Therefore, the point (ρ^*, c^*), where the bank's profit is $\pi_g^{bank}(\rho^*, c^*) = (1-\sigma)\pi_g^{bank}(\rho^0, c^0)$ for each good-type borrower, must represent the lower bound of the bank's (and consequently

fintech's) equilibrium strategy.

Proposition 1 summarizes this equilibrium characterization, with the formal proof provided in the appendix.

Proposition 1. *The following statements hold true:*

1. *No pure strategy equilibrium exists.*
2. *Payoff-equivalent mixed equilibria in undominated strategies exist, wherein all good-type borrowers receive loans, while no bad-type borrower is granted a loan.*
3. *While the bank's loan offers are secured by collateral, the fintech provides unsecured loans to borrowers with a good signal and secured loans to borrowers with a bad signal.*
4. *The bank earns strictly positive profits in all equilibria, whereas the fintech realizes strictly positive profits when* $\sigma > 0$.

In the next section, we analyze the social welfare resulting from the equilibria described in this section.

4 Welfare Effects of Open Banking

The principle of open banking is to enhance fintechs' access to borrowers' financial data, typically held by banks. As previously discussed, in our model, this improved access manifests as an increase in the quality of the fintech's signal, denoted by σ. To evaluate the welfare effects of data sharing in the loan market, we examine how market efficiency is affected by improvements in the quality of the fintech's signal.

When the fintech gains access to more data, it strengthens its position in competing with the bank, offering unsecured loans to an increased proportion of good-type borrowers. However, the fintech's marginal profit per good-type borrower decreases due to the intensified competition. The trade-off between the increase in the share of borrowers with a good signal and the fall in per borrower profit might result in cases where the fintech's profit decreases with fintech's signal quality rising above a threshold. Intuitively, for a sufficiently high γ, the bank is able to fiercely compete for the borrowers with a good

signal at the fintech such that the fall in the per borrower profit for the fintech when her signal quality increases is large. This can result in a non-monotone fintech profit as a function of her signal quality when γ is high. In contrast, the bank's competitive strength is restricted when γ is sufficiently small and hence the fall in fintech's per borrower profit for an increase in her signal quality is low. This results in a strictly increasing fintech profit as a function of her signal when γ is low.

On the other hand, when the fintech's signal quality increases, the average profit of the bank per good-type borrower, along with its market share, diminishes, leading to a decline in the bank's overall profit.

Regarding borrowers' payoffs, as outlined in Proposition 1, no bad-type borrower accepts a loan offer in equilibrium, so their utility remains zero. However, open banking benefits all good-type borrowers. Those with a good signal at the fintech receive an unsecured loan offer from the fintech and a contract with better terms from the bank. Borrowers with a bad signal also benefit from improved terms from the bank, as the bank is unable to discern their signal.

Proposition 2 summarizes the effect of open banking on the pay-offs of the borrowers and lenders.

Corollary 1. *As the quality of the fintech's signal σ increases:*

1. *The profit of the bank decreases.*
2. *There exist a γ^* such that for $\gamma \leq \gamma^*$ fintech's profit monotonically increases, and for $\gamma > \gamma^*$ fintech's profit has a maximum at some $\sigma \in [01]$.*
3. *The expected utility of all good-type borrowers rises, whereas the utility of bad-type borrowers remains unchanged at zero.*

In light of Proposition 2, it is crucial to assess the impact of an increase in σ on overall social welfare. We define social welfare as the unweighted sum of the payoffs of both lenders and borrowers, essentially the total surplus in the market. Considering that the payoff of bad-type borrowers in each equilibrium is zero, social welfare encompasses the

sum of the following components:

$$SW = \text{Bank's profit} + \text{Fintech's profit} + \text{Borrowers' payoffs}$$

As indicated in Proposition 1, good-type borrowers have access to two distinct types of loans: unsecured loans from the fintech (for those with a good signal) and secured loans (backed by collateral) from the bank. The unsecured loans offered by the fintech entail the highest possible social welfare, denoted as $\overline{SW} = \theta_g Y - 1$. However, the bank's secured contracts introduce social inefficiency due to the deadweight loss associated with collateralization.

When the quality of the fintech's signal improves, the fintech becomes capable of attracting more borrowers, leading to a substitution of some of the bank's secured contracts with more efficient unsecured loans. This substitution represents the positive impact of an increase in the fintech's signal quality on social welfare. However, as discussed earlier, since the bank is unable to differentiate between borrowers with good and bad signals at the fintech, it is compelled to offer better secured contracts to all borrowers. As depicted in Figure 2, these improved secured contracts from the bank, achievable by moving downward on the IC line, typically involve lower interest rates and higher levels of collateral, resulting in decreased social welfare. In essence, to remain competitive against a stronger fintech, the bank is forced to offer contracts that, while more favorable for good-type borrowers, are less socially efficient. Consequently, as the quality of the fintech's signal increases, some of the bank's secured contracts are replaced by those with lower social welfare. This delineates the negative impact of the increase in the fintech's signal quality on social welfare.

The foregoing discussion suggests that an increase in σ leads to a social welfare trade-off, further influenced by the cost of collateralization, γ. Specifically, when γ is high, the bank is more capable and motivated to compete for borrowers with a good signal at the fintech, resulting in contracts that entail higher levels of collateral. Conversely, when γ is low, the fintech's unsecured loans do not significantly boost social welfare, as the efficiency of the secured bank contracts they replace is already substantial.

Proposition 2 summarizes the analysis of the loan market's social welfare as a function

of the fintech's signal quality.

Proposition 2. *Consider the social welfare of the loan market equilibria as described in Proposition 1, viewed as a function of σ:*

1. *The social welfare is always increasing at $\sigma = 0$.*
2. *There exists a threshold $\hat{\gamma} \in (0, 1)$ such that:*
   (a) *If $\gamma \leq \hat{\gamma}$, social welfare is everywhere increasing in σ.*
   (b) *If $\gamma > \hat{\gamma}$, social welfare may decrease with increasing σ, exhibiting an internal local maximum and minimum, respectively.*

The maximum social welfare ($\overline{SW}$) can be attained when $\sigma = 1$, signifying that the fintech's signal is perfectly revealing. As depicted in the examples of Figure 3, social welfare always remains below that maximum level. Specifically, for any value of γ, social welfare at $\sigma = 0$ is consistently lower than this maximum (unless $\gamma = 1$). The investigation then becomes how social welfare varies with σ for any other value of σ.

The initial assertion of Proposition 2 (that is, social welfare is strictly increasing at very low σ) indicates that the beneficial impact of the fintech's unsecured loans on social welfare invariably offsets the adverse effects of the bank's more heavily collateralized loans as the fintech starts attracting good-type borrowers. Intuitively, at very low σ, the bank is not necessitated to significantly lower its interest rates through increased collateralization. Therefore, the advantageous impact of unsecured loans predominates.

As σ increases, the bank is forced to offer more appealing contracts to good-type borrowers to remain competitive against the fintech's unsecured agreements. These improved secured contracts for good-type borrowers, however, result in greater market inefficiency. According to Proposition 2, the adverse consequences of these bank offers can exceed the beneficial effects of the fintech's unsecured loans, especially if the bank's cost of collateralization is adequately low. When the bank's cost of collateral is low, i.e. high γ, secured contracts offered by the bank do not posess a high level of inefficiency and hence replacing them with unsecured loans do not dramatically increase the welfare. In other words, the positive effect of open banking on welfare is mild when γ is high. Moreover,

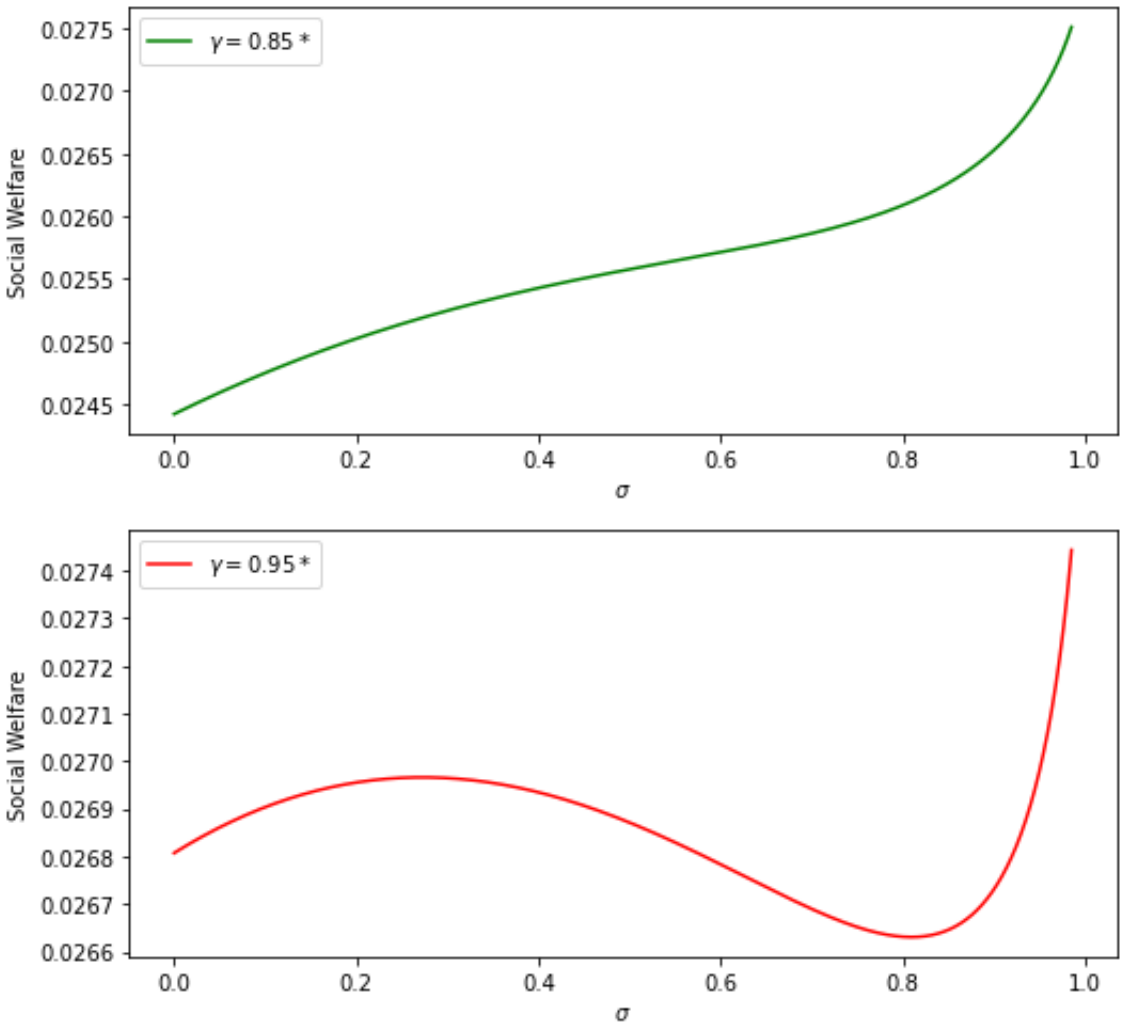

Figure 3: Social welfare in the loan market as a function of σ , ($\theta_g = 0.52$, $\theta_b = 0.48$, $Y = 2$, $\lambda = 0.7$)

the bank has more incentive and capability to compete with a strong fintech by offering collateralized loan contracts with low interest rate when γ is high. In other words, the negative effect of open banking on inefficiency through intensifying competition is strong when the cost of collateral is low for the bank.

Figure 3 showcases two scenarios. In the upper panel, γ is lower, leading to social welfare strictly increasing with σ. In the lower panel, γ is sufficiently high, causing social welfare to exhibit multi-modal behavior in σ: initially increasing, then decreasing, and subsequently increasing again before reaching its peak ($\overline{SW}$).

Another critical determinant of social welfare relative to σ is the IC line's slope, in-

fluenced by the success probability differential between the two borrower types, $\Delta\theta$. A larger $\Delta\theta$ renders the IC line steeper, thus reducing the collateral levels in the bank's secured loans. Conversely, a smaller $\Delta\theta$ flattens the IC line, necessitating higher collateral levels in the bank's contracts. Therefore, with a constant γ, the social welfare function is more likely to consistently increase with enhancements in the fintech's signal quality when $\Delta\theta$ is significant.

As demonstrated in the lower panel of Figure 3, when social welfare begins to decline with increasing σ, it encounters a local maximum and minimum. Identifying these points is essential for formulating an optimal data-sharing scheme in the loan market, ensuring the fintech's lending activities unequivocally bolster social welfare.

5 Data Sharing

As stated in Proposition 2, in our model, enhancing the quality of the fintech's signal invariably increases the payoff of good-type borrowers. Hence, in cases in which augmenting the fintech's competitive edge could detriment market efficiency, granting borrowers property rights over their financial data does not entail a decrease in social welfare. Intuitively, the influence of open banking on market efficiency hinges on the extent to which the fintech's signal precision is augmented upon making borrowers' financial data accessible.

The social welfare implications of open banking can be interpreted by considering the fintech's capacity to monitor borrowers, contingent on the quantity and type of accessible data. If the fintech could perfectly discern borrowers' types through access to their financial data, collateral-related inefficiencies would dissipate, leading to an ideal first-best allocation. Nevertheless, it's prudent to assume that the fintech's monitoring efficacy will not reach perfection, even with access to comprehensive data on each borrower. Under such circumstances, scenarios might arise where it is advantageous to allow the fintech access to only a subset of the borrowers' financial data. This regime is termed *partial data sharing*, as opposed to *full data sharing*, where the fintech gains access to the entirety of borrowers' financial data.

To formalize the discussion regarding full versus partial data sharing, let's define the extent of financial data disclosed to the fintech as $\psi \in [0, 1]$, where $\psi = 0$ implies that no data are shared and $\psi = 1$ implies that all data are shared. Let $\sigma \equiv \Phi(\psi)$ represent an increasing function, indicating that the fintech's signal precision monotonically improves with greater data access. Denote $\underline{\sigma} = \Phi(0)$ and $\overline{\sigma} = \Phi(1)$, ensuring $0 \leq \underline{\sigma} < \overline{\sigma} \leq 1$. Additionally, when the social welfare function, $SW(\sigma)$, does not monotonically increase, we denote the local maximum and minimum as σ_{max} and σ_{min}, respectively. Moreover, let $\sigma' > \sigma_{min}$ be the point where $SW(\sigma') = SW(\sigma_{max})$. The subsequent corollary encapsulates these findings:

Corollary 2. *Consider the $\hat{\gamma}$ as defined in proposition 2.*

1. *Suppose that $\gamma < \hat{\gamma}$. Then, full data sharing is optimal.*
2. *Suppose that $\gamma > \hat{\gamma}$, and social welfare function has local extremes at σ_{min} and σ_{max}:*
   - *(a) If $\overline{\sigma} < \sigma_{max}$ or $\underline{\sigma} > \sigma_{min}$, full data sharing is optimal.*
   - *(b) If $\underline{\sigma} \leq \sigma_{max} < \overline{\sigma} < \sigma'$, partial data sharing is optimal.*
   - *(c) If $\sigma_{max} \leq \underline{\sigma} < \overline{\sigma} \leq \sigma_{min}$, no data sharing is optimal.*
   - *(d) If $\underline{\sigma} > \sigma_{max}$ and $\overline{\sigma} < \sigma'$, either no or full data sharing is optimal.*
   - *(e) In any other case, partial or full data sharing can be optimal.*

Note that full data sharing is deemed optimal not only in scenarios where $SW(\sigma)$ is monotonically increasing but also in situations where it is non-monotonic, particularly when the fintech's initial monitoring quality is exceedingly low or high. As illustrated in Figure 4, even in cases of non-monotonicity, social welfare demonstrates an increasing trend in σ near the extremes of zero or one. Yet, for mid-range values of σ, the optimal strategy might lean towards partial or potentially no data sharing, depending on the changes in σ.

For instance, as shown in Figure 4, if the social welfare function does not uniformly increase with σ and $\underline{\sigma} < \sigma_{max}$, then full data sharing can only bolster social welfare if $\overline{\sigma} > \sigma'$. In essence, the optimal data sharing strategy may involve limiting the fintech's access

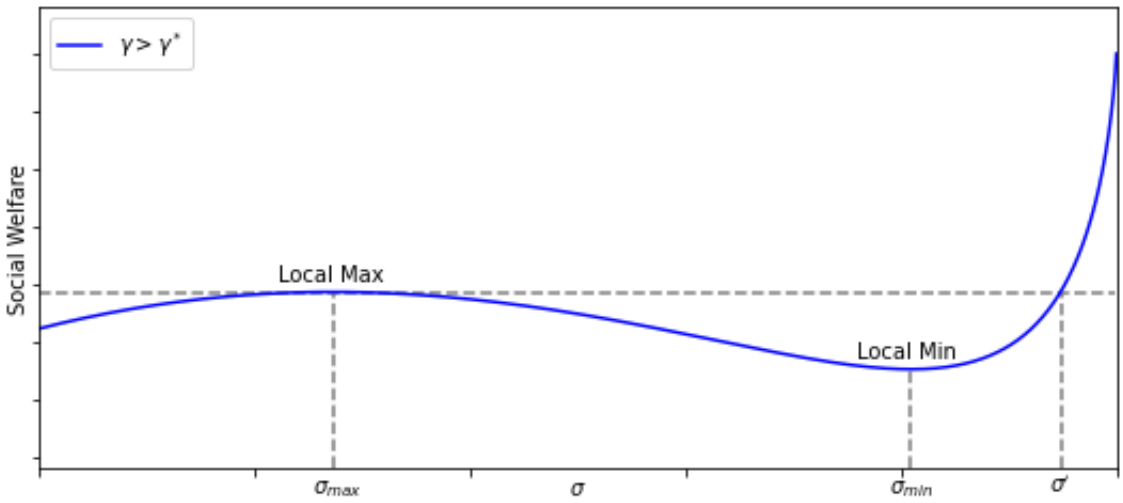

Figure 4: Optimal Data Sharing when Social Welfare is not Monotone in the fintech's Quality of Signal

to borrowers' financial data up to a certain level ψ^*, such that $\Phi(\psi^*) = \sigma_{max}$. Furthermore, given that the social welfare function may decline over a broad range of σ, there are instances where no data sharing emerges as the optimal policy. For example, in the case depicted in Figure 4, if $\sigma_{max} < \underline{\sigma} < \overline{\sigma} < \sigma_{min}$, granting the fintech access to any borrowers' data could detriment market efficiency.

From a policymaker's perspective, in situation in which the bank efficiently utilizes collateral, ensuring that open banking does not overly refine the fintech's signal accuracy beyond $\overline{\sigma} > \sigma'$ is paramount. The most effective strategy to ensure that open banking enhances social welfare under these circumstances is to implement a partial data sharing regime. This regime would equip the fintech with an amount of data that aligns with the local maximum of the social welfare function.

6 Conclusion

We model the competition in a loan market with adverse selection that consists of a bank and a fintech that are asymmetric in two dimensions; their strength in screening the borrowers, and their ability to capture the value of collateralized assets in case of default. We study the effect of open banking on the social welfare by considering an increase in the strength of the fintech in screening the borrowers due to better access to borrowers'

financial data.

In the equilibria of our model, this has two opposite effects; while open banking can empower the fintech to offer more unsecured loans and decrease the deadweight loss of collateralization, it worsens the efficiency of the bank's collateralized loans by intensifying the competition. The trade-off can result in a non-monotonic relation between the screening ability of the fintech and the market efficiency. In fact, there are cases that a certain rise in the fintech's screening potential can harm the social welfare.

Despite the simplicity of our model, the main result can hold in a more general environment. In our model, the bank is assumed to be unable to screen borrowers by processing their financial data. This normalization does not seem to play a role in our main result. If the bank can screen borrowers and identify some of them as good-type, his loan offers to those borrowers must be unsecured and so without inefficiency. Hence, the competition of the bank and the fintech on those borrowers can not affect the social welfare, since both lenders' contracts are optimal. In fact, the main trade-off between unsecured loans of the fintech and heavily collateralized loans of the bank that results from the intensified competition when the fintech has better access to the borrowers' data will still be in place, as long as lenders are not able to perfectly identify all borrowers' types.

Furthermore, we assume a signal structure that does not allow for false negatives; a borrower with a good signal is certainly of a good-type. If the fintech wrongly considers some bad-type borrowers as credible borrowers with a high probability of repayment, we will have another type of inefficiency in the equilibrium resulting from granting loans to bad-type borrowers. Therefore, a non-monotic relationship between fintech's access to data and the social welfare is more likely with a generalized signal structure. In other words, if the technology of the fintech is not perfect in identifying borrowers with a low probability of repayment, open banking can further reduce the efficiency of the market by enabling the fintech to offer loan contracts to the borrowers with low payment probability.

While our paper contributes to the growing literature on the effects of open banking on the lending markets, it also relates to the literature on information design in the digital economy. Since a rise in fintech's screening ability always enhances the borrowers' surplus in our model, giving the ownership of the data to the borrowers can not prevent

the cases where open banking harms the market efficiency. From the policy point of view, our results encourage the design of a more sophisticated data sharing regime in the loan markets.

A Omitted Proofs

It is useful to introduce some notation before proceeding to the proofs.

Definition 1. *We define* $H : \{(\rho, c)|U_b(\rho, c) = 0\} \to R^+$ *such that:*
if $r = H(\rho, c)$*, then* $U_g(r, 0) = U_g(\rho, c)$*.*

We define the social welfare of each contract with a good-type borrower as $sw(\rho, c) = \pi_i^k(\rho, c) + U_i(\rho, c)$, and denote the highest possible social welfare in a contract as $s\bar{w} = \theta_g Y - 1$.

To ease the notational burden, we write the profits and social welfare of any contract as a function of $U_g(\rho, c)$, the utility of the good type borrower. For any contract on the IC line, we have $U_b = 0$ which implies $Y - \rho = \frac{1-\theta_b}{\theta_b} c$. Then the utility of a good-type borrower from such a contract can be written as $c(\frac{\theta_g - \theta_b}{\theta_b})$. The social welfare of a contract between lender k and a good-type borrower on the IC can also be written as $sw_{IC}^k = s\bar{w} - (1 - \theta_g)(1 - \gamma^k)c$. Hence, the social welfare of any contract on the IC line can be written as:

$$sw_{IC}^k(\rho, c) = SW_{IC}^k(U_g(\rho, c)) = s\bar{w} - U_g(\rho, c)\frac{(1 - \theta_g)(1 - \gamma^k)\theta_b}{\theta_g - \theta_b}$$

.

We define $\zeta^k \equiv \frac{(1-\theta_g)(1-\gamma^k)\theta_b}{\theta_g - \theta_b}$, and so $sw_{IC}^k(\rho, c) = sw_{IC}(U_g(\rho, c)) = s\bar{w} - \zeta^k U_g(\rho, c)$.

Similarly, we can write the profit of the lenders on the IC line as
$\pi_{IC}^k(\rho, c) = s\bar{w} - (\zeta^k + 1)U_g(\rho, c)$,

while the profit of the lenders from an unsecured contract with a good-type borrower writes
$\pi_{us}^k(\rho, c)) = s\bar{w} - U_g(\rho, c)$.

Thus, defining $x(\rho, c) \equiv U_g(\rho, c)$, we can write:
$sw_{IC}^k(\rho, c) = sw_{IC}^k(x(\rho, c)) = sw_{IC}^k(x) = s\bar{w} - \zeta^k x$
$\pi_{IC}^k(\rho, c) = \pi_{IC}^k(x(\rho, c)) = \pi_{IC}^k(x) = s\bar{w} - (1 + \zeta^k)x$
$\pi_{us}^k(\rho, 0) = \pi_{us}^k(x(\rho, 0)) = \pi_{us}(x) = s\bar{w} - x$.

Let's also denote

$$\underline{x} \equiv x(\rho^0, c^0) = s\bar{w}(1 - \frac{\theta_b(1-\theta_g)}{\theta_g(1-\theta_b)}).$$

Also, knowing that

$$\pi_g^{bank}(\rho^*, c^*) = s\bar{w} - (1+\zeta^{bank})x* = (1-\sigma)\pi_g^{bank}(\rho^0, c^0) = (1-\sigma)(s\bar{w} - (1+\zeta^{bank})\underline{x}),$$

we define

$$x^* \equiv x(\rho^*, c^*) = \underline{x} + (\frac{s\bar{w}}{1+\zeta^{bank}} - \underline{x})\sigma.$$

and denote $\alpha \equiv \frac{s\bar{w}}{1+\zeta} - \underline{x}$, where $\zeta = \zeta^{bank}$. Note that α is always positive for non-zero ζ.

Proof. of Proposition 1:

I- First consider the case where $\sigma = 0$. With the conventional rationing rule, if both lenders offer for example (ρ^0, c^0), half of the borrowers accept each lender's offer, and therefore the bank can deviate by offering a contract lower on the IC line. Hence, with a continuous space for pay-offs, a pure strategy equilibrium does not exist. Furthermore, for $\sigma > 0$, the fintech can attract borrowers with a good signal and have a non-negative profit by any contract $(\rho^{fin}, 0)$ such that $\frac{1}{\theta_g} < \rho^{fin} < H(\rho^0, c^0)$, which is not possible without an informative signal. For any pure strategy of the bank that earns him a positive profit, the fintech can offer an unsecured contract slightly better for the good-type borrowers and attract the ones with a good signal. On the other hand, for any pair of pure strategies such that $\pi_g^{bank}(\rho, c) < (1-\sigma)\pi_g^{bank}(\rho^0, c^0)$, the bank prefers to give up the borrowers with good signal and offer (ρ^0, c^0). Hence, at least one lender has a profitable deviation from any pair of pure strategies.

II, III- First note that in the absence of any informative signal, any contract to the left of the IC line will be accepted by the bad-type borrowers and incur losses to the lenders. On the other hand, any contract at the right side of the IC line can be matched by a contract on the IC line such that the utility of the good-type borrower is preserved while the profit of the lender increases. Hence, the equilibrium strategy of the bank who does not have an informative signal must be on the IC line. The same argument applies for the fintech's

offers to the borrowers with a bad signal. Also note that, since there is no false positive in the signal structure of the fintech, offering a contract with collateral to the borrowers with a good signal is sub-optimal for the fintech.

Consider the case when $\sigma = 0$. As mentioned in section 3.1, the bank can prevent the fintech from having positive profit by offering (ρ^0, c^0) where $\pi_g^{fin}(\rho^0, c^0) = 0$. Therefore, we can have mixed equilibria in undominated strategies such that the bank offers (ρ^0, c^0) and the fintech offers randomized contracts on the IC line above this point such that the bank has no incentive to offer more profiting contracts. (we specify this kind of mixed strategies in the following lines.)This implies that the upper bound of the support for the bank's strategy which lays on the IC line must be (ρ^0, c^0), preventing the fintech from gaining positive profit from a good-type borrower without having an informative signal about them.

For any $\sigma > 0$, if the fintech offers unsecured contracts to the borrowers with a good signal such that $U_g(\rho^{fin}, 0) > U_g(\rho^0, c^0)$, the bank will have the profit $\lambda(1-\sigma)\pi_g^{bank}(\rho^0, c^0)$ if he keeps his offer at (ρ^0, c^0). Let's denote (ρ^*, c^*) the contract from which the bank has the profit $\pi_g^{bank}(\rho^*, c^*) = (1-\sigma)\pi_g^{bank}(\rho^0, c^0)$. Since this is the best offer the bank is willing to make to compete for the borrowers with good signal, it must be the lower bound of the bank's strategy support. Hence we denote the bank's strategy support as:

$$S^{bank} = \{(\rho, c)|\ U_b(\rho, c) = 0, U_g(\rho^0, c^0) \leq U_g(\rho, c) \leq U_g(\rho^*, c^*)\}.$$

As argued above, in the equilibrium, the fintech must offer loans without collateral to the borrowers with good signal, while offering contracts on the IC line above (ρ^0, c^0) to the borrowers with a bad signal. Hence, according to the support of the bank's strategy, the fintech's strategy support should be

$$S_{-\sigma}^{fin} = \{(\rho, c)|\ U_b(\rho, c) = 0, U_g(\rho, c) > U_g(\rho^0, c^0)\}$$

, for the borrowers with a bad signal, and

$$S_{\sigma}^{fin} = \{(\rho, 0)|\ U_g(\rho^0, c^0) \leq U_g(\rho, 0) \leq U_g(\rho^*, c^*)\}$$

, for the borrowers with a good signal.

Let's denote the strategy distribution of the lenders on the support of their strategy as:

$$F^k(\rho_0, c_0) = F^k(x(\rho_0, c_0)) = Pr\{x(\rho, c) \leq x(\rho_0, c_0)\}.$$

We also denote the strategy distribution of the fintech for the borrowers with a good and bad signal as F_{σ}^{fin} and $F_{-\sigma}^{fin}$, respectively.

Following the argument about the support of lenders' strategy, we know that $F^{bank}(x^*) = 1$. Hence if the fintech offers contract $H(\rho^*, c^*)$ such that $x(H(\rho^*, c^*)) = x^*$, she gains the profit $\lambda\sigma(s\bar{w} - x^*)$. For any unsecured loan offer of the fintech to the borrowers with a good signal, her profit writes:

$$\Pi_{\sigma}^{fin}(x(\rho, 0)) = \lambda\sigma F^{bank}(x)(s\bar{w} - x).$$

Hence, the indifference condition for the mixed strategy equilibria implies that

$$F^{bank}(x) = \frac{s\bar{w} - x*}{s\bar{w} - x}.$$

Note that the equilibrium strategy of the bank has a mass point at (ρ^0, c^0), with the size of $\frac{s\bar{w} - x*}{s\bar{w} - \underline{x}}$.

Also, according to the strategy support of the fintech, in the equilibrium, we must have $F_{\sigma}^{fin}(x^*) = 1$, $F_{\sigma}^{fin}(\underline{x}) = 0$, and $F_{-\sigma}^{fin}(\underline{x}) = 1$. If the bank offers contract (ρ^*, c^*), he gains the profit $\Pi_g^{bank}(x^*) = \lambda(1-\sigma)\Pi_g^{bank}(\underline{x}) = \lambda(1-\sigma)(s\bar{w} - (1+\zeta)\underline{x})$. The profit of the bank from any loan contract in his support writes:

$$\Pi^{bank}(x(\rho, c)) = \lambda[(1-\sigma)\pi_g^{bank}(x) + \sigma F_{\sigma}^{fin}\pi_g^{bank}(x)].$$

Therefore, the indifference condition for the mixed strategy equilibria implies that:

$$F_{\sigma}^{fin} = \frac{(1-\sigma)(1+\zeta)(x - \underline{x})}{\sigma(s\bar{w} - (1+\zeta)x)}.$$

To specify $F_{-\sigma}^{fin}$, we write the following condition which assures that the bank has no incentive to offer contracts above (ρ^0, c^0) on the IC line:

$$\Pi^{bank}(\rho, c) = \lambda(1-\sigma)F_{-\sigma}^{fin}\pi_g^{bank}(\rho, c) < \lambda(1-\sigma)\pi_g^{bank}(\rho^0, c^0),$$

for any (ρ, c) such that $x(\rho, c) < x(\rho^0, c^0)$. So any $F_{-\sigma}^{fin}$ that satisfies:

$F^{fin}_{-\sigma}(x) < \frac{s\bar{w}-(1+\zeta\underline{x})}{s\bar{w}-(1+\zeta x)}$ and $F^{fin}_{-\sigma}(\underline{x}) = 0$, can be an equilibrium strategy.

Note that although this part of the fintech's equilibrium strategy is not unique, no borrower accept these offers and they only work as a threat to prevent the bank from offering contracts above (ρ^0, c^0) on the IC line. Thus, all the equilibria characterized above are pay-off equivalent.

The profit of the lenders in the equilibrium is:

$$\Pi^{bank} = \lambda(1-\sigma)\pi^{bank}_g(\rho^0, c^0) = \lambda\pi^{bank}_g(\rho^*, c*) = \lambda(s\bar{w} - (1+\zeta)x^*)$$

, and

$$\Pi^{fin} = \lambda\sigma\pi_{us}(\rho^*, c^*) = \lambda\sigma(s\bar{w} - x*)$$

, which are positive for $1 < \sigma < 1$.

□

Proof. of Corollary:

I- $\Pi^{bank} = \lambda(1-\sigma)(s\bar{w} - (1+\zeta)x*)$

$\frac{\partial\Pi^{bank}}{\sigma} = -(s\bar{w} - (1+\zeta)x^*) - (1+\zeta)(1-\sigma) \leq 0, \quad \text{for } \sigma \in [01].$

II- $\Pi^{fin} = \lambda\sigma(s\bar{w} - x*)$

$\frac{\partial\Pi^{fin}}{\partial\sigma} = \lambda(s\bar{w} - \underline{x} - 2\alpha\sigma)$

Note that for $\gamma \to 1$ we have $\zeta \to 0$ and $\alpha \to s\bar{w} - \underline{x}$ and hence Π^{fin} has a maximum at $\sigma = \frac{1}{2}$. It is easy to check that the fintech's profit has a maximum for a $\sigma \in [0\ 1]$ if $\frac{s\bar{w}-\underline{x}}{2\alpha} \leq 1$, which implies that $\zeta \leq \frac{s\bar{w}-\underline{x}}{s\bar{w}+\underline{x}}$. Hence, there exist a γ^* such that for $\gamma \geq \gamma^*$, we have $\zeta \leq \frac{s\bar{w}-\underline{x}}{s\bar{w}+\underline{x}}$, and fintech's profit has a maximum for a $\sigma \in [0\ 1]$.

III- Note that while the upper-bound of the strategy supports in the equilibrium are increasing in the quality of the fintech's signal, $\frac{\partial x^*}{\partial\sigma} > 0$, both probability distribution functions of the lenders' strategies in the equilibrium are decreasing in the quality of the fintech's signal:

$\frac{\partial(dF^{bank}(x))}{\partial\sigma} < 0,$

$\frac{\partial(dF_\sigma^{fin}(x))}{\partial\sigma} < 0$.

This implies that with σ increasing, both lenders replace some of their loan offers by contracts that are of higher utility for the borrowers. Hence, the expected utility of the borrowers must increase.

□

Proof. of Proposition 2:

We can write the social welfare of the market equilibrium described in proposition 1 as:

$$SW = \lambda[\int_{\underline{x}}^{x^*} \sigma F^{bank}(x) s\bar{w}\, dF^{fin}(x) + \int_{\underline{x}}^{x^*} (\sigma F^{fin}(x) + (1-\sigma))(s\bar{w} - \zeta x)\, dF^{bank}(x)],$$

where

$$dF^{bank}(x) = \frac{s\bar{w} - x^*}{(s\bar{w} - x)^2}.dx,$$

and

$$dF^{fin}(x) = \frac{(s\bar{w} - (1+\zeta)x^*)(1+\zeta)(1-\sigma)}{\sigma(s\bar{w} - (1+\zeta)x)^2}.dx.$$

The first term is the social welfare of the loan contracts of the fintech, and the second term is the social welfare of the bank's contracts. Calculating the integral and simplifying, we have:

$$SW(\sigma) = \left(s\bar{w} + (1-\sigma)(\alpha\sigma - \zeta\underline{x})\right) + \left((1-\sigma)(s\bar{w} - \underline{x} - \alpha\sigma)(\frac{s\bar{w} - (1+\zeta)\underline{x}}{\zeta s\bar{w}})\ln(\frac{(1-\sigma)(s\bar{w} - \underline{x})}{s\bar{w} - \underline{x} - \alpha\sigma})\right),$$

as the social welfare of the loan market equilibrium as a function of the quality of the fintech's signal.

The first derivatives writes:

$$SW'(\sigma) = \left(\zeta\underline{x} - 2\alpha\sigma\right) - \left((\alpha(1-2\sigma) + s\bar{w} - \underline{x})(\frac{s\bar{w} - (1+\zeta)\underline{x}}{\zeta s\bar{w}})\ln(\frac{(1-\sigma)(s\bar{w} - \underline{x})}{s\bar{w} - \underline{x} - \alpha\sigma})\right)$$

Note that while the first expression which is linear can become negative as σ increases, the second expression is always non-negative. Also ote that $SW'(0) = \zeta\underline{x} \geq 0$ and $SW'(1) = +\infty$.

The second derivative writes:

$$SW"(\sigma) = -2\alpha[1 + (\frac{s\bar{w} - (1+\zeta)\underline{x}}{\zeta s\bar{w}}) \ln(\frac{(1-\sigma)(s\bar{w} - \underline{x})}{s\bar{w} - \underline{x} - \alpha\sigma})]$$

$$-(\alpha(1-2\sigma) + s\bar{w} - \underline{x})(\frac{s\bar{w} - (1+\zeta)\underline{x}}{\zeta s\bar{w}})(\frac{\alpha + \underline{x} - s\bar{w}}{(1-\sigma)(s\bar{w} - \underline{x} - \alpha\sigma)})$$

Note that

$$SW"(0) = -2\alpha - (\frac{(s\bar{w} - (1+\zeta)\underline{x})(s\bar{w} - \underline{x} - \alpha)^2}{\zeta s\bar{w}(s\bar{w} - \underline{x})}),$$

which can be simplified to

$$SW"(0) = -2\alpha + \alpha(\frac{\zeta s\bar{w}}{(1+\zeta)(s\bar{w} - \underline{x})}).$$

We know that $s\bar{w} - (1+\zeta)\underline{x} > 0$, which implies that $\frac{\zeta s\bar{w}}{(1+\zeta)(s\bar{w}-\underline{x})} < 2$.

Therefore, $SW"(0) < 0$.

Note that $SW"(\sigma)$ monotonically increases to $+\infty$ at $\sigma = 1$. Therefore the second derivative has a unique root. let's denote this unique root of the second derivative as σ^*. Note that at $\sigma = 0$, the first derivative is positive and the second derivative is negative, while at $\sigma = 1$ both derivatives are positive. If the sign of the first derivative at the unique root of the second derivative is positive, then the function must be monotonically increasing in σ. Conversely, if $SW"(\sigma^*) < 0$, meaning that the sign of the first derivative at the unique root of the second derivative is negative, it implies that the function $SW(\sigma)$ becomes decreasing.

We know that at σ^* we must have:

$$(\frac{s\bar{w} - (1+\zeta)\underline{x}}{\zeta s\bar{w}}) \ln(\frac{(1-\sigma^*)(s\bar{w} - \underline{x})}{s\bar{w} - \underline{x} - \alpha\sigma^*}) =$$

$$1 + (\alpha(1-2\sigma^*) + s\bar{w} - \underline{x})(\frac{s\bar{w} - (1+\zeta)\underline{x}}{2\alpha\zeta s\bar{w}})(\frac{\alpha + \underline{x} - s\bar{w}}{(1-\sigma^*)(s\bar{w} - \underline{x} - \alpha\sigma^*)}).$$

Replacing into the expression for the first derivative and simplifying, we get

$$SW"(\sigma^*) = \frac{(\alpha(2\sigma^* - 1) - s\bar{w} - \underline{x})^2}{2(1-\sigma^*)(s\bar{w} - \underline{x} - \alpha\sigma^*)} - \alpha(\zeta + 2)$$

First note that for $\gamma = 0$, we have $\alpha = 0$ and $SW(\sigma^*) = \frac{s\bar{w}-\underline{x}}{2(1-\sigma^*)} > 0$. As γ approaches 1, ζ tends to 0 and α tends to $s\bar{w} - \underline{x}$ from below. This implies that the first term in the

above expressions tends to 2α from below where the second term tends to 2α from above. Hence, $SW(\sigma^*)$ approaches zero from below when γ is sufficiently close to 1. Then there must exit γ^* such that for $\gamma > \gamma^*$, we have $SW(\sigma^*) < 0$.

Given that $SW'(\sigma)$ is the sum of a linear decreasing and a convex increasing function, and $SW'(0) \geq 0$ while $SW'(1) = +\infty$, it can have either zero or two roots. Hence, for $\gamma > \gamma^*$, where we have $SW(\sigma^*) < 0$, the social welfare function must have a local maximum and then a local minimum when σ goes from 0 to 1.

□

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