Collateral, Information and Welfare: Implications for Open Banking*

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Abstract

Data sharing (such as open banking initiatives) and improvements in data analytics enhance the capabilities of financial technology (fintech) companies and have the potential to reduce information asymmetries in credit markets. This is generally believed to alleviate adverse selection and improve welfare. Traditional lenders (such as banks), however, respond to increasing competition by offering more attractive products that involve costly collateral. We uncover a novel trade-off between improved information and destructive competition due to increased collateralization. For instance, we show that open banking or advances in data analytics may harm not only social welfare but also fintechs themselves. We also examine alternative institutional arrangements—such as the allocation of property rights and the creation of data markets—that can outperform open banking. Our results contribute to the ongoing policy debate on the welfare implications of open banking and data-sharing initiatives.

KEYWORDS: Information, collateral, data sharing, open banking, fintechs, banks, welfare

JEL CLASSIFICATION: D82, L13, G21, G23

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1 Introduction

It is well established that financial markets are characterized by asymmetric information, which often leads to distortions and inefficiencies. In their seminal paper, Stiglitz and Weiss (1981) show that adverse selection can lead to credit rationing and potential underinvestment.[1] A substantial body of subsequent theoretical and empirical research has confirmed and extended these insights, highlighting the central role of information asymmetries in financial frictions. As a result, the production and dissemination of information that alleviates these asymmetries can have profound effects on market efficiency and investment outcomes.

Improvements in information and prediction arise from various sources. Perhaps the most important is the accumulation and dissemination of personal and other types of data, alongside the expansion of data centers, more powerful processors, and larger storage capacities. The countless online activities and digital connections that take place each day give rise to vast amounts of data that have reshaped the economy. The rise of artificial intelligence (AI) and data analytics has further accelerated this transformation. Better and better-trained algorithms allow lenders to make more accurate predictions about potential borrowers. In this new landscape, financial technology companies (fintechs) leverage technology and the increasing availability of data to offer a wide range of financial services, including—but not limited to—banking, payment processing, investment management, and insurance.[2]

Given their growing importance, new legislative frameworks—such as the GDPR[3] and the CCPA[4]—have been introduced to regulate the collection and processing of personal data. Their main goal is to ensure that the ownership of information generated through consumers' digital activities is returned to the consumers themselves. In the context of financial markets, a more specific initiative—known as *open banking*—aims to "support innovation and competition in retail payments and enhance the security of payment transactions and the protection of consumer data." Open banking has the potential to reshape financial markets by enabling new entrants, such as fintechs, to compete with

[1] Subsequent contributions have shown that under- or over-investment is possible. For instance, de Meza and Webb (1987) show that over-investment is a possible equilibrium outcome.

[2] Greck et al. (2018) shows that the growth of fintech lending is driven by both regulatory arbitrage and technological innovation. Using mortgage data, they find that shadow banks—including fintechs—gained substantial market share from 2007 to 2015, with over half of the growth explained by lighter regulation and about a third by technology-enabled efficiency. For further discussion on the definition and evolution of fintechs, see Giglio et al. (2021).

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

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

traditional financial intermediaries in the provision of banking services.[5]

Open banking and the rise of new technologies that enhance the dissemination of information and improve predictive accuracy have the potential to redistribute market power and significantly reshape financial markets. This evolution raises several economically significant questions. For instance, does the availability of more information—perhaps through data-sharing initiatives such as open banking—necessarily benefit borrowers and lenders? If so, under what conditions? If not, are there alternative institutional arrangements that could lead to better market outcomes and improved welfare? What are the incentives of lenders to improve accuracy?

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 initiate. 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 creditworthy projects. Additionally, entrepreneurs have a fixed quantity of a physical asset at their disposal, which can serve as collateral should they opt for a loan.[6]

Our model features two key characteristics. First, we assume that lenders face a cost in collateralizing the physical asset. As in Bester (1985) and Boot et al. (1991), we assume that—due to transaction costs, legal expenses of foreclosure, political frictions, or other factors—the collateralized asset is worth more to borrowers than to lenders.[7] A pivotal assumption in our model, however, is that the bank holds a comparative advantage over the fintech in leveraging collateral as a means of securing loans. This advantage stems from the bank's institutional experience and legal infrastructure and is supported by em-

[5]Babina et al. (2025) shows that open banking indeed successfully promotes fintech entry. In particular, using a difference-in-differences design, they show that the number of VC-backed fintech financings increases by one-third and the total amount of capital invested doubles following the adoption of open banking policies.

[6]Collateral can take different forms. For example, short-term loans are sometimes collateralized by accounts receivable, in which case the lender seizes the borrower's cash flow if the borrower fails to fulfill their obligation. Some fintechs provide loans that are repaid directly through revenue collections. In these cases, the value of collateral to the lender is almost equal to that to the borrower. Given that a key feature of our model is that the value of collateral differs between lenders and borrowers—and that the two lenders are differentiated—our framework applies more directly to settings involving physical collateral such as real estate, equipment, or inventory.

[7]For instance, borrowers may derive greater utility from the asset because it is part of a productive enterprise or due to personal attachment (e.g., a primary residence). See Djankov et al. (2008), who estimate the combined costs associated with pledging and enforcing collateral across OECD countries. See Elyasiani and Goldberg (2004) for more details on collateral in credit markets.

pirical evidence.[8] Our model, therefore, applies better to loans to small firms (SME, SBA, etc.), as, for example, in Gambacorta et al. (2022), which considers SME loans obtained either by MYbank (a fintech) or traditional commercial banks.[9]

The second key component of our model is that the fintech is more capable than the bank in analyzing data from public sources or previous transactions and, hence, is able to make better predictions. In particular, we assume that the fintech can, with some probability (σ), identify whether a borrower is creditworthy. This probability measures the fintech's informational strength and market power. The advantage of fintechs over banks in analyzing data is well-documented.[10] To sum up, we study competition between a collateral-dependent bank and an information-reliant fintech.

Naturally, given that the two lenders are differentiated, no pure strategy equilibrium exists. By contrast, we characterize the unique mixed-strategy equilibrium (in non-dominated strategies).[11] In Section 3, we show that, in equilibrium, the bank randomizes over a set of secured loans, while the fintech randomizes over a set of unsecured loans. Recent empirical studies are, in fact, consistent with this equilibrium outcome.[12] In equilibrium, only high types borrow—either by selecting a secured loan from the bank or an unsecured loan from the fintech.

Our main objective in this paper is to study the welfare consequences of strengthening the precision of the signal received by the fintech (σ). In other words, we are interested in

[8]In an early theoretical contribution, Manove et al. (2001) highlights the intrinsic preference of banks for collateralized lending. Empirically, Cerqueiro et al. (2020) examines an exogenous transfer of priority rights from banks to other creditors and shows that this shift affects future corporate financing, suggesting that banks have an advantage in utilizing collateral.

[9]In Gambacorta et al. (2022), collateral primarily refers to tangible assets—most notably real estate—used to secure bank loans. By contrast, big tech lenders offer mostly unsecured credit and instead rely on alternative data sources to assess creditworthiness.

[10]For instance, Balyuk and Gurun (2023) shows that fintechs strategically invest in information acquisition—such as bank transaction and spending data—to reduce adverse selection. Similarly, Berg et al. (2020) demonstrates that digital footprint data can predict loan defaults as accurately as traditional credit scores. Fuster et al. (2019b) finds that fintech mortgage lenders process loans faster and with lower default rates than traditional banks, even after controlling for borrower risk. These findings suggest that fintechs' technological infrastructure and access to alternative data sources enhance their predictive capabilities relative to traditional lenders.

[11]As discussed in the main part of the paper, our equilibrium shares features with the mixed-strategy equilibrium characterized in Blume (2003) and is reminiscent of the price dispersion model in Varian (1980).

[12]Empirical studies consistently show that banks overwhelmingly rely on collateralized lending. For instance, Benmelech et al. (2024a) documents that around 60% of firms with commercial bank loans in the U.S. have those loans secured. Pozzolo (2002) and Berger and Udell (1990) further find that banks are more likely to demand collateral from riskier or less established borrowers, highlighting its role in mitigating information asymmetries. Recent evidence from Gupta et al. (2023) shows that for small firms—especially those in the lowest size deciles—the majority of bank loans are backed by real estate, reinforcing the centrality of collateral in bank lending practices. In contrast, recent studies such as Gambacorta et al. (2022) and Gopal and Schnabl (2022) show that fintech lenders rarely require collateral.

how welfare is affected by improvements in information. Such improvements can stem from data transfers (e.g., open banking initiatives), enhancements in data analytics, or other technological developments. In Section 4, we study the welfare of the different market participants, as well as total welfare, as a function of the informativeness of the signal (σ).

A critical feature of the equilibrium in our model is that improvements in the fintech's signal precision alter the market structure. In particular, an increase in σ strengthens the fintech's competitive position and compels the bank to offer more attractive contracts to borrowers. These more attractive contracts, however, involve higher collateral requirements. Therefore, there is a trade-off between the benefits of more information—namely, more borrowers obtaining non-collateralized loans—and the downside of fiercer competition, which induces higher-collateral loan offers. It is this trade-off that underlies our welfare results.

As better information intensifies competition, borrowers benefit and enjoy higher welfare.[13] By contrast, a more powerful fintech reduces the bank's profit. For the fintech itself, the effect is more subtle: when the bank's value of collateral is low, the bank has limited capacity to respond, and the fintech's profit increases with σ. When the bank's collateral value is high, the relationship becomes non-monotonic—excessive competition can reduce the fintech's profit if σ is too high.

As for total welfare, the effects depend on the value of collateral. When the bank's collateral value is low, improvements in information reduce the reliance on costly collateral and thus enhance welfare. However, when the collateral value is high, the fintech's competitive pressure can lead the bank to demand more collateral, which may reduce overall welfare—that is, welfare can decline as σ increases.

In Section 5, we study the implications of our results for open banking, the establishment of data markets (i.e., Laudon 1996), and improvements in data analytics. For instance, recent empirical evidence (Babina et al., 2025; Nam, 2022) documents that open banking indeed reduces adverse selection, leads to an expansion of credit, and affects welfare.[14] We establish conditions under which open banking can enhance the welfare of market participants. Perhaps surprisingly, we find that open banking does not always

[13] As shown in Section **??**, if borrowers experience an intrinsic privacy cost—i.e., higher σ entails the use of more personal data—then borrower welfare may no longer be strictly increasing in σ and could instead exhibit an inverse U-shape. Nonetheless, all our main results remain robust.

[14] Nam (2022) analyzes loan-level data from a German fintech lender and finds that customer data sharing improves credit allocation—particularly for riskier borrowers—by increasing approval rates, lowering interest rates, and reducing default. Together, these studies underscore how data portability can reduce information frictions and expand financial access through more accurate screening and enhanced competition.

improve total welfare and might even be harmful for fintechs. In situations where open banking may not be optimal, we show that market efficiency can sometimes be improved by restraining the flow of data to fintechs to a certain optimal level. This implies that open banking with full data sharing is not necessarily the optimal arrangement; some type of restriction in the processing and flow of data might, in fact, enhance welfare. To the best of our knowledge, these novel results contribute to the debate on open banking by highlighting that data sharing can have unintended consequences—opposite to those expected by policymakers.

We then consider alternative data-sharing institutions, such as the allocation of property rights and the establishment of a market for data. For instance, early work by Laudon (1996) envisioned the emergence of "National Information Markets," where individuals could sell their personal data.[15] We find that while the allocation of property rights is sometimes irrelevant for welfare, in other cases, assigning property rights over data to lenders may lead to better outcomes. We derive implications for when this would be optimal. For example, we conjecture that in advanced economies with strong lender protection laws and judicial systems, open banking might be dominated by an alternative institution in which lenders are allocated the property rights and can trade in a well-established market for data.

Related Literature. The literature on fintechs' challenging the banking sector is growing fast. In what follows, we mention a few recent and closely related articles.

The most related work to our paper is He et al. (2023). Similarly to our paper, they model competition between a bank and a fintech. Unlike our paper, these authors do not allow for any screening device (such as collateral). He et al. (2023) demonstrates 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 market efficiency. Our paper complements their result in the sense that we provide conditions under which open banking can deteriorate total welfare while increasing borrowers' surplus.[16]

[15] More recent contributions have explored how data markets can be designed to balance efficiency, privacy, and fairness. For example, Jentzsch (2019) discuss decentralized data markets and their regulatory implications, while Bergemann et al. (2019) analyze how market design affects welfare when data is traded. Ichihashi (2020) further investigates how platforms can optimally price access to consumer data in competitive environments.

[16] In terms of more technical details, in He et al. (2023) the fintech earns zero profits before open banking whilst the bank earns zero profits after open banking. This is because open banking determines who has a more informative signal; hence, the lender with the most informative signal earns strictly positive profits whereas the lender with the least informative signal earns zero profits. In our paper, both lenders earn

Jing (2021) explores a similar 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 et al. (2025) 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.

Another closely related work that studies the consequences of an open banking regime is Parlour et al. (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.

Vives and Ye (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 are aligned with their insight about the potential adverse effects of intensified competition in the credit market, our model differs mainly by considering the technological differences of banks and fintechs in mitigating the credit market inefficiencies due to adverse selection.

In related work, Jones and Tonetti (2020) and Dosis and Sand-Zantman (2024) study the allocation of property rights over online-generated data. Jones and Tonetti (2020) argues that assigning data ownership to consumers can increase the number of firms that

strictly positive profits. In an extension of the model, we allow the bank to have a signal and show that this is irrespective of whether the fintech or the bank has a more informative signal. We also consider cases in which the fintech has a less informative signal after open banking. In this case, we show that open banking is always welfare-improving.

gain access to the data, thereby promoting competition and potentially enhancing economic growth. Dosis and Sand-Zantman (2024) shows that the optimal allocation of data rights depends on the value of data: when data value is low, both users and firms prefer users to hold the rights; when data value is high, both sides may favor firm ownership, even if users incur higher privacy costs. Our paper relates to this literature by showing that, when a market for data exists, the allocation of property rights can influence welfare outcomes. Unlike Dosis and Sand-Zantman (2024) we consider multiple sellers (i.e., lenders) and allow these to trade property rights.

The remainder of the paper is organized as follows. Section 2 presents the baseline model. In Section 3, we characterize the unique undominated equilibrium in mixed strategies. Section 4 analyzes the welfare of the different market participants as a function of the informativeness of the signal. Section 5 discusses the implications of the model for open banking, property rights allocation, and improvements in data analytics. In Section **??**, we examine several extensions of the model and show that our results are robust. Section 6 concludes. All formal proofs are relegated to the appendix.

2 Model

Preliminaries

There are two time periods (today and tomorrow) and a single good. We will use the terms "good", "cash" and "dollars" interchangeably to represent the same thing. The net risk-free interest rate between these two periods is exogenously given and denoted by r. All agents in the economy are risk-neutral and do not discount the future. Consequently, all agents share the same preferences over (possibly random) consumption streams $(\tilde{c}_1, \tilde{c}_2)$ across the two periods, represented by

$$u(\tilde{c}_1, \tilde{c}_2) = \mathbb{E}[\tilde{c}_1] + \mathbb{E}[\tilde{c}_2],$$

where $\mathbb{E}[\cdot]$ denotes the expectation operator.

Entrepreneurs

There is a continuum of entrepreneurs of measure one. Entrepreneurs can be of two types: high and low, indexed by $i \in \{H, L\}$. The share of type i entrepreneurs in the population is $\lambda^i \in (0, 1)$, with $\lambda^L + \lambda^H = 1$. For notational simplicity, we let $\lambda^H \equiv \lambda$. The entrepreneur's type (i) is (a priori) her private information.

Each entrepreneur has a project that requires 1 dollar today to initiate and yields a random return $\tilde{Y}$ dollars tomorrow. The expected return of the project depends on the entrepreneur's type. Specifically, the project yields $\tilde{Y} = Y$ with probability θ^i, and $\tilde{Y} = 0$ with probability $1 - \theta^i$, where $\Delta\theta \equiv \theta_H - \theta_L > 0$. Let $\theta^\circ \equiv \lambda^H\theta^H + \lambda^L\theta^L$ denote the average probability of success—this also corresponds to the fraction of entrepreneurs whose projects succeed if all undertake them. We assume that the outcome of the project (i.e., the realized state) is observable and verifiable in a court of law. We further make the following assumption:

$$\frac{r}{\theta^H} < Y < \frac{r}{\theta^\circ}. \tag{1}$$

This assumption has several important implications, which we discuss below. First, since $\theta^L < \theta^\circ$, it implies that while high types possess projects with strictly positive net present value (NPV), low types possess projects with strictly negative NPV. Hence, low types should not undertake their projects, as doing so imposes a social cost.[17] Furthermore, the assumption implies that no lender would be willing to offer loans indiscriminately — without additional information, such indiscriminate lending would be unprofitable.

Entrepreneurs are endowed with physical assets that can serve as collateral. The collateral level is the same for all entrepreneurs and equal to $\bar{C}$. This means that if an entrepreneur keeps her collateral until tomorrow, she can earn $\bar{C}$ in dollars. We assume that $\bar{C}$ is sufficiently high to enable effective screening.

Lenders

There are two types of lenders in our economy: a traditional bank and a fintech company, indexed by $\zeta = \{B, F\}$. Each lender can raise funds inelastically at the risk-free interest rate (r) and can provide one-dollar loans to borrowers, where loans are in the form of secured debt. Specifically, a loan contract is represented by a pair $x = (R, C)$, where R 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 the borrower defaults. Given our assumption that the outcome of the project is observable and verifiable, it is natural that contracts can be perfectly enforced ex post such that there is no strategic default.

Consistent with the assumption in Bester (1987), we posit that collateralizing assets incurs costs. These costs can be a combination of transaction costs (appraisal, legal, monitoring), risk costs (illiquidity, depreciation, foreclosure delays), and regulatory capital

[17] Although not necessary for our results, this assumption simplifies the analysis. Allowing projects by low types to have positive NPV would imply that both types are granted loans in equilibrium, which is not the case under the information structure we consider below.

requirements. In particular, a lender needs to incur appraisal and legal costs before signing the contract to estimate and ensure the value of a collateralized asset. Moreover, in the event of a default, a lender might capture 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, which constitutes an implicit social cost.[18]

To provide an estimate, note that empirical evidence shows that the cost of collateralizing physical assets in OECD countries is nontrivial. Djankov et al. (2008) estimates that, across OECD jurisdictions, the combined costs associated with creating, registering, and enforcing collateral—including fees, legal expenses, administrative delays, and foreclosure-related inefficiencies—range from approximately 3% to 12% of the asset's real value.[19]

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, thanks 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 firms, by leveraging their established relationships. As highlighted in the introduction, this assumption is supported by empirical evidence. For example, Cerqueiro et al. (2020) demonstrates the collateralization advantage of banks compared to other creditors. Furthermore, studies such as Gambacorta et al. (2022) and Gopal and Schnabl (2022) underscore that fintechs rarely provide collateralized loans, which is also confirmed by the results of our paper.[20] Without loss of generality and to economize on notation, we assume that in case the bank provides a collateralized loan and seizes the collateral, it earns a (per unit of collateral) value $\gamma_B \equiv \gamma$, where $\gamma \in (0, 1)$, whereas the fintech earns a (per unit of collateral) value $\gamma_F = 0$.[21]

The payoffs of type i from signing contract x and lender ζ from signing contract x with

[18]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.

[19]To bring these insights into a more recent context, the World Bank's *Doing Business 2020* indicators for resolving insolvency in high-income OECD economies indicate that the direct cost of recovering debt measures on average around 9% of the debtor's estate. See World Bank, *Doing Business 2020: Resolving Insolvency. Available at:* *https://archive.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB12-Chapters/Resolving-Insolvency.pdf*

[20]We show below that in equilibrium, fintechs offer unsecured loans whereas banks offer loans backed up by collateral.

[21]As we mentioned above, the assumption that the (per unit of collateral) value for the fintech is zero is without loss of generality. All our results hold as long as the per unit values of the two lenders satisfy the following inequality: $0 \leq \gamma_F < \gamma_B < 1$.

type i are given respectively by:

$$U^i(x) = \theta^i \max\{Y - R + \bar{C}, \bar{C}\} + (1 - \theta^i) \max\{\bar{C} - C, 0\} \tag{2}$$

and

$$\Pi^i_\varsigma(x) = \theta^i R + (1 - \theta^i) \min\{C, \bar{C}\}. \tag{3}$$

We assume that borrowers accept loan contracts with strictly positive expected payoff, and they choose randomly if they are indifferent between two loan contracts.[22]

Information

Our goal is to study how information affects market outcomes and welfare. In particular, we assume that only the fintech receives a signal for each entrepreneur who applies for a loan: $S \in \{S^+, S^-\}$. The assumption that fintechs obtain and rely on informational signals—rather than on traditional lending channels—is well-grounded. 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." Thus, the core of the fintech business model is built around predictive data analytics, further justifying our assumption that fintechs (and, to a lesser extent, traditional banks) receive informative signals.

The probability that the fintech receives signal S for a type-i entrepreneur is denoted by $\sigma^i(S) \geq 0$, where $\sigma^i(S^+) + \sigma^i(S^-) = 1$.

In the main part of the paper, we focus on a *false negatives (or partially inconclusive) signal structure*, which in our model corresponds to the assumption that $\sigma^H(S^+) \geq 0$ and $\sigma^L(S^+) = 0$ (See also Figure 1). In plain English, this means that the fintech may receive a negative signal even if the entrepreneur is of high type, but can never receive a positive signal if the entrepreneur is of low type. This immediately implies that upon receiving a positive signal, the fintech can perfectly identify that the entrepreneur is of high type. Given this signal structure, and with some abuse of notation, we denote $\sigma^H(S^+) \equiv \sigma$. Although in the main part of the paper, we assume that only the fintech receives a signal and is *partially inconlusive*, this assumption is by no means necessary for our results.[23]

[22]The modeling of competition between lenders with different costs of collateral has characteristics similar to Bertrand price competition with asymmetric marginal costs. As shown below, we follow Blume (2003) to find the mixed-strategy equilibria under the conventional demand sharing rule. We could replace this rationing rule by positing that, when indifferent between two loan contracts, borrowers choose the contract offered by the bank without changing the qualitative features of our results.

[23]In Section **??**, we discuss the robustness of our results in two extensions. First, in a model in which the bank also receives a signal. Second, in a model in which the fintech has a more general signal structure.

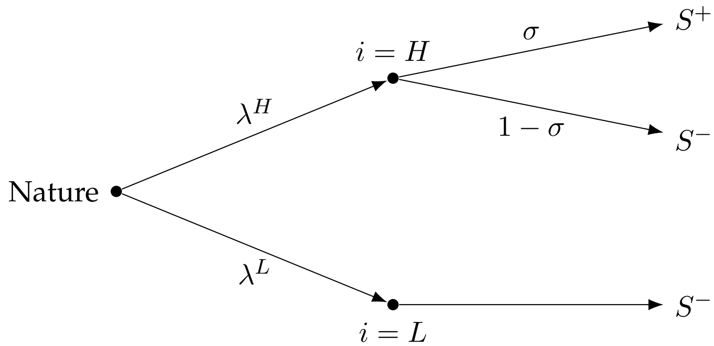


Figure 1: **The signal structure.** If the type is low, the fintech receives signal S^- with certainty; if the type is high, the fintech receives signal S^+ with probability σ and signal S^- with the complementary probability.

Given the assumption that the average project has strictly negative net present value (NPV), another implication of the assumed signal structure is that the fintech may offer an uncollateralized loan to an entrepreneur upon receiving a positive signal, but any such loan would necessarily yield a strictly negative profit if the signal is negative. Consequently, upon observing a negative signal, the fintech can only offer collateralized loans.

Timing of Events

The timing of events is specified below:

- **Stage 0**: Nature selects the type of every entrepreneur and every entrepreneur privately learns their type.
- **Stage 1**: The two lenders publicly offer signal-contingent loan contracts.[24] Entrepreneurs observe the contracts offered by both lenders.
- **Stage 2**: Each entrepreneur's signal from each lender is realized and privately observed by the entrepreneur and the corresponding lender.
- **Stage 3**: Entrepreneurs choose one of the two lenders or decide not to borrow. If an entrepreneur chooses to borrow, the game proceeds to the next stage.
- **Stage 4**: The entrepreneur receives funds under the contract corresponding to the offer made in *Stage 1* and the signal realized in *Stage 2*, and invests in the project.

[24]In the baseline model, the bank has no signal and thus offers unconditional contracts; the fintech offers a menu of contracts—one for entrepreneurs who receive a positive signal and one for those who receive a negative signal.

- **Stage 5**: If the project succeeds, the entrepreneur repays R; if it fails, the lender seizes the collateral C.

Under this timing, the two lenders publicly announce their menus, which are conditional on the entrepreneurs' realized signals. Entrepreneurs then observe their signals and choose whether to apply to one of the two lenders or to opt out and sign no contract.[25] Once a contract is selected, the entrepreneur invests in their project, and payments are executed based on the realized outcome.

A key assumption in our model is that while each lender knows the signal structure of their competitor, they do not observe the signal that an entrepreneur receives from the competing lender. Given our assumptions, this means that although the bank knows σ, it does not observe the signal of the fintech for any of the entrepreneurs. Notably, the fintech has a strict incentive to treat its signals as proprietary information. This is because if the bank observed the signal received by the fintech, the two lenders would compete a la Bertrand wiping out any positive profits. Given that, as we show below, in equilibrium, the fintech earns strictly positive profits for any informative signal, the fintech's profit strictly decreases if its signals are observed by the bank. This implies that the fintech strictly prefers to keep its signals private.

We analyze the perfect Bayesian equilibria (PBE) of the model. A strategy for a lender specifies a menu of contracts, contingent on the signal received by the borrower. A strategy for an entrepreneur specifies, for each type and signal realization, whether to accept a contract from one of the lenders or to keep their collateral and abstain from borrowing. A PBE consists of strategy profiles for all lenders and entrepreneurs such that: (i) each lender maximizes its expected profit given the strategies of the entrepreneurs and the other lender; and (ii) each entrepreneur maximizes their expected utility given the strategies of the lenders.

3 Equilibrium

In this section, we study the equilibria of the game. Figure 2 will significantly facilitate our exposition. The figure depicts the contract space, along with the indifference curves of the two types and the zero-profit lines of the two lenders. The steep (red) line originating at Y represents the set of contracts for which the low type is indifferent between applying

[25] A game that yields qualitatively similar results is one in which, in the first stage, lenders privately observe signals about each entrepreneur and offer personalized (private) loan contracts. In the second stage, entrepreneurs choose one of those contracts or opt out.

for a loan and not borrowing:

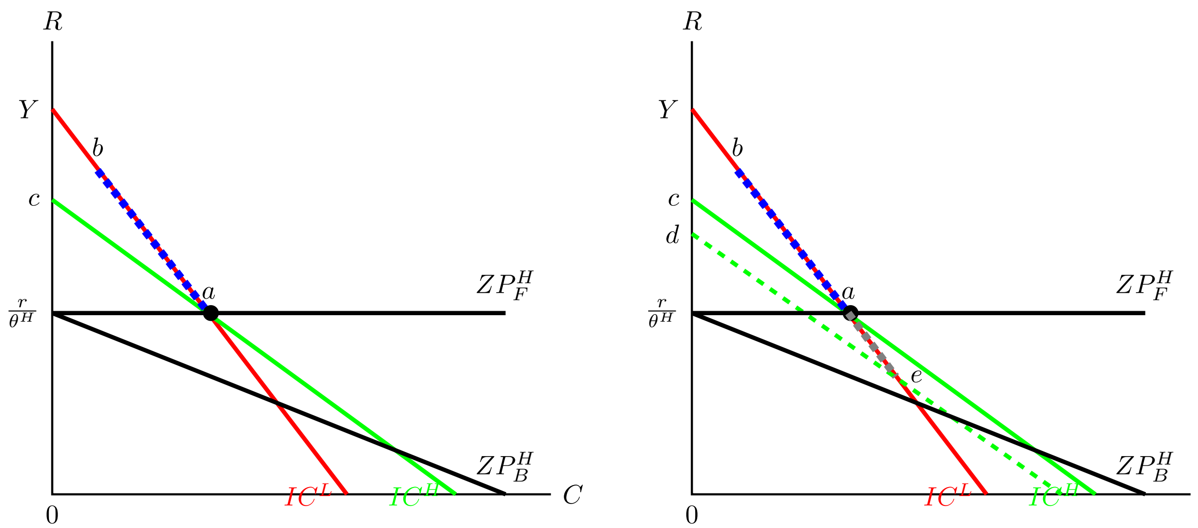
$$\theta^L(Y-R)-(1-\theta^L)C+\bar{C}=0 \tag{IC^L}$$

The less steep (green) line starting at c is an indifference curve for the high type:

$$\theta^H(Y-R)-(1-\theta^H)C+\bar{C}=\bar{U}^H. \tag{IC^H}$$

The horizontal line beginning at r/θ^H and the steeper black line—also starting at r/θ^H–are the fintech's and bank's zero-profit lines:[26]

$$\theta^H R+(1-\theta^H)\gamma_\zeta C-r=0. \tag{ZP^H_ζ}$$



(a) $\sigma=0$

(b) $\sigma>0$

Figure 2: **Graphical representation of the equilibrium.**

The easiest and most pedagogical way to understand the equilibrium is to begin with a hypothetical scenario in which both lenders face the same cost of collateralizing assets, and the fintech has a completely uninformative signal as in the seminal paper of Bester (1985). Recall that, under Assumption 1, any lender would like to exclude all the low types. Therefore, the lenders would like to offer a contract on the right of line (IC^L). Due to competition among lenders, the unique equilibrium entails both lenders offering a single collateralized contract that targets the high types as depicted by contract a in Figure 2a.[27]

[26]Recall that the fintech assigns zero value to collateral, hence its profit lines are horizontal.

[27]Note that this is essentially a variant of the Rothschild and Stiglitz (1976) least-cost separating equilibrium in which the two lenders earn zero profits, the high type accepts a collateralized loan and the low type stays out. Assumption (1) guarantees that no profitable deviation exists because every contract that attracts both types will necessarily yield strictly negative profits.

Now assume that the fintech's signal remains uninformative, but suppose that $0 = \gamma_F < \gamma = \gamma_B$. In this case, the bank has a clear advantage over the fintech due to its lower cost of collateralization. Ideally, the bank would like to offer the most profitable contract, but it is constrained by the competitive threat posed by the fintech. Because the two lenders are asymmetric, a pure strategy equilibrium does not exist. For any pair of contracts offered by the two lenders, there always exists a profitable deviation as in the logic classic Bertrand game with asymmetric sellers.

The unique mixed-strategy equilibrium (in non-dominated strategies) is illustrated in Figure 2a. In this equilibrium, the bank offers contract a, which is selected by the high types whilst all low types refrain from borrowing. The fintech acts as a competitive threat, randomizing among contracts (b, a). Neither lender has an incentive to deviate. The bank is weakly worse off offering any alternative contract that would attract high types and improve profits relative to a and is weakly worse offering any contract above a because it will earn a higher per-borrower profit but its offer will be accepted with a lower probability. In this equilibrium, the fintech does not attract any borrower but has no profitable devation: any contract better than a will necessarily yield losses.[28]

Now suppose that the fintech's signal is informative—that is, $\sigma > 0$. The fintech is able to identify a share of high-type entrepreneurs; this allows it to attract them away from the bank by offering a contract slightly below point c in Figure 2a. The bank, in turn, will attempt to respond by offering a contract on the IC^L line that attracts all borrowers. This dynamic implies that a pure strategy equilibrium cannot be sustained. Unlike the case where $\sigma = 0$, however, the bank now randomizes over collateralized contracts.

Point e in Figure 2b represents the contract that, if accepted by all high types, yields the same profit to the bank as contract a would yield if taken only by the share of high types who receive a negative signal from the fintech (i.e., $1 - \sigma$). In other words, the bank is indifferent between attracting all high types at contract e or attracting only the $1 - \sigma$ share at contract a. Suppose now that the bank plays contract a with some non-zero probability (i.e., there is a mass point at a) such that the fintech is indifferent across the entire segment $(c, d]$—that is, between offering a contract that attracts only the high types with a positive signal at point c, or all such types at point d.

We can fully characterize probability distributions for the two lenders such that the bank randomizes over contracts in the segment $[a, e]$, placing a mass point at a, while the

[28] The nature the equilibrium in this setting shares key features with the classic Bertrand duopoly, in which two asymmetric firms with linear costs (a low-cost and a high-cost firm) compete by posting prices for a homogeneous product. Under the standard market-sharing rule—where the firm with the lower price captures the entire market, and equal prices lead to a split of demand—it is well known that a pure strategy equilibrium fails to exist. See Blume (2003) and the remarks after Proposition 1.

fintech offers contracts in the segment $(c, d]$ to entrepreneurs with a positive signal, and contracts in $[b, a]$ to those with a negative signal—such that no profitable deviation exists. As in the $\sigma = 0$ case, the bank is weakly worse off offering any contract above a (since those offered by the fintech act as a credible threat) or below a (as this would increase the share of high types attracted but reduce per-unit profits). Likewise, the fintech cannot profitably offer contracts above c—as they would attract no borrowers (who would instead choose the bank)—or below d, which would increase the borrower share but reduce per-unit profits.

The following proposition summarizes the unique equilibrium in undominated strategies in this game.

Proposition 1. *There exists a unique mixed-strategy equilibrium in undominated strategies in which the bank offers loans backed up by collateral whereas the fintech offers loans backed up by collateral to entrepreneurs with the negative signal and non-collateralized loans to entrepreneurs with the positive signal. In equilibrium, only the high-type entrepreneurs borrow either from the bank with collateral or from the fintech without collateral.*

Remarks

1. In the classic model of Bertrand competition with asymmetric firms, Blume (2003) shows that a mixed-strategy equilibrium exists in which the low-cost firm sets a price equal to the high-cost firm's marginal cost, while the high-cost firm randomizes over higher prices. In other words, the high-cost firm acts as a competitive threat to the low-cost firm. Blume (2003) further shows that apart from this equilibrium, alternative equilibria exist that involve dominated strategies. In these equilibria, the low-cost firm selects a price below the marginal cost of the high-cost firm randomizes over a set of higher prices, thereby acting as a competitive threat.

   Similar equilibria arise in our model. In particular, one can construct equilibria in which the bank randomizes over less-profitable contracts. As in Blume (2003), these equilibria involve dominated strategies. For this reason, we focus on equilibria in undominated strategies, as formally characterized in Proposition 1. The equilibrium we focus on is not only in undominated strategies but is also the unique equilibrium that yields the highest social welfare because it entails the least possible collateral.

2. It is worth noting that our model shares key features with the seminal paper by Varian (1980). In Varian's model, two sellers of a homogeneous good face two groups of buyers: informed buyers, who are aware of both sellers, and uninformed (or

captive) buyers, who are aware of only one. Each seller aims to attract as many informed buyers as possible without sacrificing their captive buyers. This creates a trade-off: attracting more informed buyers requires lowering prices, which in turn reduces the profit extracted from uninformed buyers. The resulting equilibrium is in mixed strategies, with each seller randomizing over a set of prices in such a way that they earn exactly the profit they would obtain by selling only to their uninformed customers.

A similar mechanism arises in our setting. Since the bank has a comparative advantage in collateralizing assets, any entrepreneur with a negative signal can be viewed as ”uninformed” from the bank's perspective. In particular, the bank can profitably offer contract a (as shown in Figure 2) to such entrepreneurs. Conversely, entrepreneurs who receive a positive signal from the fintech can be seen as ”informed”—the group over which the two lenders compete. The equilibrium is again in mixed strategies: each lender randomizes over a set of contracts such that the bank is indifferent across offers and earns a profit equal to what it would obtain by attracting only the uninformed borrowers at contract a.

4 Welfare Effects of Information

Our primary interest in this paper lies in understanding how improvements in information affect equilibrium outcomes and welfare. Given our information structure, it is relatively straightforward that a higher σ is associated with "better information." Indeed, a higher σ implies that the fintech can more accurately identify the type of any entrepreneur it interacts with; for instance, if $\sigma = 1$, the fintech is perfectly informed.[29]

Let the entrepreneurs' expected payoff be denoted by $U(\sigma)$, and the payoffs of the bank and the fintech by $\Pi_B(\sigma)$ and $\Pi_F(\sigma)$, respectively.[30] Total welfare is then given by:

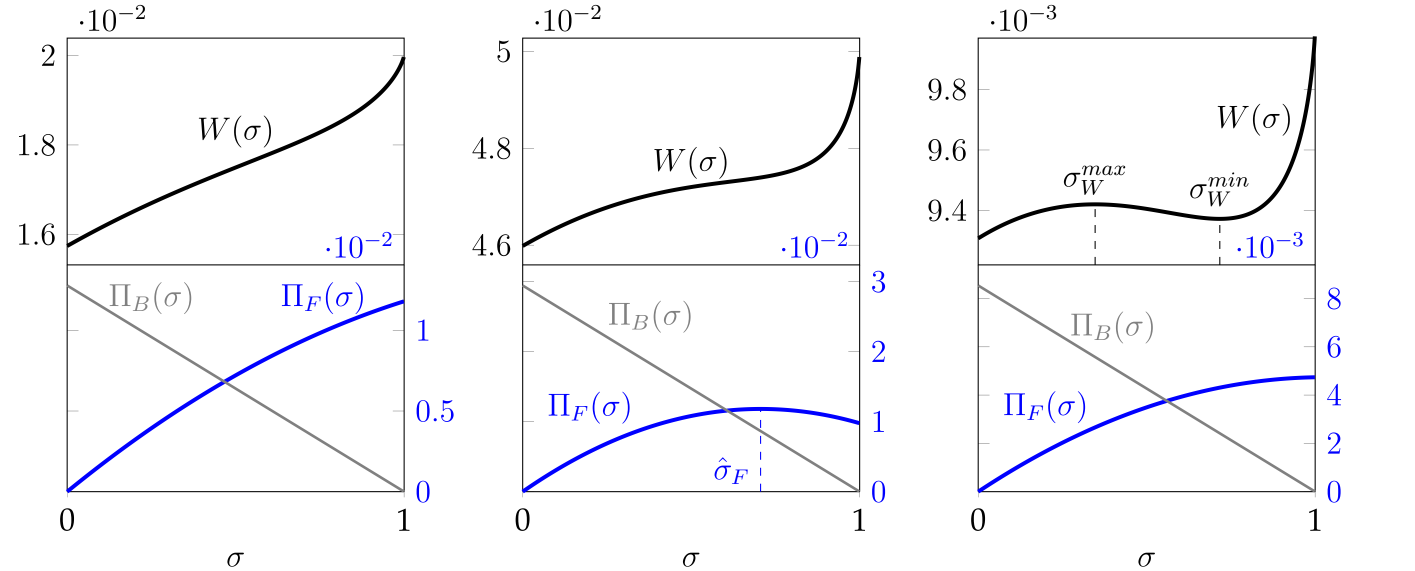
$$W(\sigma) = U(\sigma) + \Pi_B(\sigma) + \Pi_F(\sigma),$$

which corresponds to the welfare of a utilitarian social planner.

We begin by examining how a change in σ affects entrepreneurs—that is, we are interested in the shape of $U(\sigma)$. Recall that σ denotes the probability that the fintech correctly

[29] Note that a higher σ implies that, conditional on the entrepreneur being of high type, the probability of being correctly identified as high increases; similarly, if the entrepreneur is of low type, the conditional probability of being identified as low also increases.

[30] We consider the *ex ante* payoff of entrepreneurs—that is, before they learn their types. Given that, for any parameter values, only the high types borrow, the payoff of the low types does not depend on σ. Therefore, the *ex post* payoff of the high types is $U(\sigma) - \lambda_B \bar{C}$.



(a) $\gamma < \min\{\gamma_F, \gamma_W\}$ (b) $\gamma_F < \gamma < \gamma_W$ (c) $\gamma_W < \gamma < \gamma_F$

Figure 3: **Total Welfare and lenders' profits as a function of the fintech's signal quality (σ).** (a) $Y = 2$, $\theta^H = 0.52$, $\theta^L = 0.48$, $\lambda = 0.5$, $\gamma = 0.75$. (b) $Y = 2$, $\theta^H = 0.55$, $\theta^L = 0.45$, $\lambda = 0.5$, $\gamma = 0.88$. (c) $Y = 2$, $\theta^H = 0.51$, $\theta^L = 0.49$, $\lambda = 0.5$, $\gamma = 0.925$.

identifies a high-type entrepreneur. As expected, an increase in σ allows the fintech to identify a larger share of high types and thereby expand its effective demand. In response, the bank competes by offering more attractive contracts to those entrepreneurs who are identified by the fintech. This intensifies competition between the two lenders, each seeking to attract the high-type borrowers. As a result, an increase in σ strictly improves the payoff of the high types.[31]

We now examine the effect of σ on the profits of the two lenders. First, note that the effect of σ on the bank's profit is unambiguously negative. A higher σ implies that the fintech can make more attractive offers and thus capture a larger share of the market at the bank's expense. Therefore, $\Pi_B(\sigma)$ is strictly decreasing in σ.

For the fintech, the effect of changes in σ is more nuanced. There are two competing forces at play. First, the *direct effect*: an increase in σ enables the fintech to identify more high-type entrepreneurs and thereby expand its market share. Second, there is an *indirect effect*: as σ increases, per-customer profit decreases, because the bank responds to the heightened competition by offering more attractive contracts, which forces the fintech to improve its own offers as well.

[31]This result relies on the assumption that entrepreneurs face no privacy cost. If, for example, a higher σ implied greater intrusion into privacy, then the effect of an increase in σ could be twofold: it would intensify competition—leading to more attractive offers and thus higher entrepreneur welfare—but also raise privacy costs, which would tend to reduce welfare. We discuss this trade-off in Section XX.

For sufficiently low values of σ, the direct effect dominates: increases in σ improve the fintech's position without substantially eroding per-unit profits. However, for higher values of σ, the fintech's profit becomes increasingly sensitive to the bank's counteroffers. The overall effect on $\Pi_F(\sigma)$ then depends critically on the parameter γ, which captures the bank's per-unit value of collateral.

Recall that a lower γ implies that the bank finds it more difficult to compete through collateralized contracts, which reduces its market power. In this case, the fintech enjoys a competitive advantage, and its profit $\Pi_F(\sigma)$ is strictly increasing in σ. As γ increases, however, the bank is better able to respond with more attractive collateral-based offers, thereby regaining market share. This diminishes the fintech's competitive edge. Hence, there exists a critical threshold γ_F above which the fintech's profit becomes inverse-U shaped in σ: initially increasing due to the direct effect, but eventually decreasing as the indirect competitive pressure dominates.

We can equivalently examine the effect of σ on total welfare. As noted earlier, entrepreneurs always benefit from increases in σ, while the bank's payoff strictly decreases. The effect on the fintech, however, is ambiguous. From a welfare perspective, two forces are at play. The first is a *direct effect*: as σ rises, a greater share of entrepreneurs obtain non-collateralized loans, thereby avoiding costly collateral requirements. The second is an *indirect effect*: higher values of σ intensify competition, forcing the bank to respond by offering contracts with higher collateral requirements. When γ is low, the direct effect dominates, so welfare increases with σ. By contrast, when γ is high, the indirect effect may dominate, and welfare can decline as σ rises. Hence, there exists a threshold value γ_W such that for $\gamma \leq \gamma_W$, welfare is strictly increasing in σ, while for $\gamma > \gamma_W$, the relationship between welfare and σ may turn negative.[32]

Proposition 2. *The following results hold regarding the effect of σ on payoffs and welfare:*

1. ***(Entrepreneurs)** The payoff of the entrepreneurs, $U(\sigma)$, is continuous and strictly increasing in σ.*

2. ***(Lenders)** The bank's profit, $\Pi_B(\sigma)$, is strictly decreasing in σ. Moreover, there exists a threshold $\gamma_F \in (0,1)$ such that:*

    (a) For $\gamma \leq \gamma_F$, the fintech's profit $\Pi_F(\sigma)$ is strictly increasing in σ.

    (b) For $\gamma > \gamma_F$, the fintech's profit $\Pi_F(\sigma)$ is inverse U-shaped in σ.

[32]The threshold values γ_F and γ_W are not necessarily comparable; they are context-dependent. Depending on the parameter configuration, γ_F can be either lower or higher than γ_W. Examples are presented in Figures 3b and 3c.

3. ***(Total Welfare)*** *There exists a threshold $\gamma_W \in (0,1)$ such that:*

   (a) *For $\gamma \leq \gamma_W$, total welfare $W(\sigma)$ is strictly increasing in σ.*

   (b) *For $\gamma > \gamma_W$, total welfare $W(\sigma)$ is bimodal, exhibiting an interior local minimum and an interior local maximum in $\sigma \in (0,1)$.*

Figure 3 represents different cases for the profit and total welfare functions depending on the parameters. For instance, in Figures 3a and 3b, total welfare is strictly increasing is σ, whilst in Figure 3c, total welfare is bimodal and exhibits a local maximum (σ_W^{max}) and a local minimum (σ_W^{min}). In Figures 3a and 3c, the profit of fintech is strictly increasing in σ, whereas in Figure 3b, the profit is inverse U-shaped attaining an interior global maximum at ($\hat{\sigma}_F$).

In the following section, we discuss the implications of these results in various settings.

5 Implications

We now derive several implications from the results established in the previous section. To do so, we assume that $\sigma \in [\underline{\sigma}, \overline{\sigma}]$, where $0 \leq \underline{\sigma} < \overline{\sigma} < 1$. This reflects the fact that the informativeness of the signal may vary depending on the institutional environment (as discussed below). To understand how different levels of informativeness arise, we must address two important and interrelated questions: (i) why fintechs (and more generally, lenders) are able to acquire information about potential borrowers, and (ii) how the prediction of borrower creditworthiness is improved.

The primary source of information for lenders is data analytics. This data may be publicly available—such as information shared on social networks, cookies, and other digital traces—or proprietary, including detailed financial records such as a borrower's wealth, assets, credit history, and digital footprints. For instance, a lender may possess confidential information about specific borrowers, either from prior lending relationships or through external data sources.[33] Analyzing such data enables lenders to partially infer a borrower's type. We therefore interpret $\underline{\sigma}$ as reflecting the fintech's baseline technology (e.g., access to public data or social media), while $\overline{\sigma}$ corresponds to the highest achievable predictive accuracy given existing technological and data-processing capabilities.

Improvements in information quality—i.e., increases in σ—can arise from two main sources: (i) expanded access to borrower data (e.g., through open banking initiatives or

[33]Examples include soft information accumulated through lending relationships (Petersen and Rajan, 1994) and access to shared credit histories via credit bureaus (Pagano and Jappelli, 1993).

data-sharing arrangements), and (ii) advances in data analytics that enhance predictive accuracy. That is, predictions improve either because of higher data input into a given technology or improvements in the technology (e.g., improvement in algorithms) itself. According to empirical evidence, lenders can significantly improve their prediction of borrower creditworthiness by leveraging digital footprints, alternative data sources, and machine learning techniques (Berg et al., 2020; Fuster et al., 2019a).

In what follows, we examine the different possibilities in detail.

5.1 Data Transfers: Implications for Open Banking and Data Markets

5.1.1 Open Banking

The adoption of the *(Revised) Payment Services Directive* (known as PSD2)[34] provided the legal framework governing data ownership and sharing within the European Union. PSD2 requires European banks to offer automated access to customer transaction accounts—subject to customer consent—to qualified third parties via API technology.[35] This initiative, commonly referred to as *open banking*, aims to "support innovation and competition in retail payments and enhance the security of payment transactions and the protection of consumer data."

Under open banking, entrepreneurs (i.e., borrowers) hold full property rights over their generated data and may transfer these data between lenders at will. Suppose, for instance, that entrepreneurs have accumulated transaction (legacy) data from previous interactions with the bank, which they can choose to transfer to the fintech. The fintech may then use these data to improve its prediction of borrower type. Naturally, more data enable better prediction—i.e., a higher value of σ. At one extreme, no data sharing (closed banking) results in the lowest possible signal precision, $\underline{\sigma}$; at the other, full data sharing (open banking) yields the highest possible prediction, $\overline{\sigma}$.

Recall from Proposition 2 that the entrepreneurs' payoff $U(\sigma)$ is strictly increasing in σ. It follows that entrepreneurs strictly prefer to transfer their data to the fintech, assuming that doing so improves prediction.[36] To keep the analysis tractable, we do not formally

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

[35] This access applies to both retail and corporate customers. APIs enable synchronization and interconnection of databases. Within the banking system, APIs link a bank's database (which stores customer information) with various applications and services, allowing the delivery of personalized products and payment solutions. See Giorgio et al. (2018), pp. 43–46.

[36] Note that this result depends crucially on the assumption that entrepreneurs face no intrinsic privacy cost when sharing their data. If privacy costs were present, open banking could have either a positive or negative impact on their welfare.

model the data transfer decision. Instead, we assume that under open banking, the fintech has access to the entrepreneur's data before making any offer.[37]

Regarding lender profits, Proposition 2 shows that the bank is always worse off as σ increases. Therefore, open banking unequivocally reduces the bank's profit. For the fintech, however, the effect is ambiguous. As shown in Proposition 2, when γ is sufficiently low, the fintech's profit $\Pi_F(\sigma)$ is strictly increasing in σ, whereas for high γ, it is inverse U-shaped. Thus, open banking may either benefit or hurt the fintech. Let

$$\hat{\sigma}_F \in \underset{\sigma \in [\underline{\sigma}, \overline{\sigma}]}{arg\,max}\, \Pi_F(\sigma) \tag{4}$$

denote the signal that maximizes the fintech's profit.

At one extreme, for $\hat{\sigma}_F = \overline{\sigma}$, open banking benefits the fintech as its profit is strictly increasing in the amount of data it receives. At the other extreme, for $\hat{\sigma}_F = \underline{\sigma}$, the fintech would strictly prefer closed banking. In any other case, *open banking with partial data sharing* may yield better outcomes than full data sharing. Specifically, suppose that $\hat{\sigma}_F \in (\underline{\sigma}, \overline{\sigma})$—that is, the fintech's profit function $\Pi_F(\sigma)$ is inverse U-shaped.[38] Then, the fintech would strictly prefer to have access to only a subset of the data. Since more data increase σ, and the optimal point is interior, partial data sharing would be optimal from the fintech's perspective.[39]

A similar logic applies to total welfare. Recall from Proposition 2 that $W(\sigma)$ is either strictly increasing or bimodal, with both a local minimum and a local maximum in the interior. Let

$$\hat{\sigma}_W \in \underset{\sigma \in [\underline{\sigma}, \overline{\sigma}]}{arg\,max}\, W(\sigma) \tag{5}$$

denote the signal that maximizes total welfare. Then, the same conclusions follow: full data sharing (i.e., open banking with $\sigma = \overline{\sigma}$) may or may not be welfare-maximizing, depending on whether $\hat{\sigma}_W = \overline{\sigma}$ or lies in the interior of the interval.

Proposition 3 (Open Banking and Welfare)**.** *The welfare and distributional effects of open banking depend critically on the informativeness of the signal and the value of collateral:*

[37] This assumption corresponds to an equilibrium outcome. Suppose, for example, there is a preliminary stage (prior to Stage 0) in which entrepreneurs decide whether to allow the fintech access to their data. In the continuation game, entrepreneurs anticipate that a higher σ increases their expected payoff, and thus choose to share the data. Even if the decision were made after types are realized, a standard unraveling argument implies that both types would eventually agree to share their data.

[38] Reconsider Figure 3c and suppose that $\underline{\sigma} < \hat{\sigma}_F < \overline{\sigma}$.

[39] It is worth mentioning that, several jurisdictions already implement forms of restricted data access in open banking. For example, the EU's PSD2 framework allows banks to provide access through tiered APIs with different scopes of data (e.g., account information only vs. payment initiation). Similarly, some platforms use throttling, rate limits, or require purpose-specific consent to control the flow and granularity of data. For a discussion of tiered access models and data governance, see Carullo (2021), Zetzsche et al. (2020a), and Carr and Thakor (2023).

1. ***(Entrepreneurs)*** *Entrepreneurs always benefit from open banking with full data sharing.*

2. ***(Bank)*** *The bank strictly prefers closed banking.*

3. ***(Fintech)*** *If $\hat{\sigma}_F = \overline{\sigma}$, the fintech prefers open banking with full data sharing. In all other cases, it may prefer either partial data sharing or closed banking.*

4. ***(Welfare)*** *If $\hat{\sigma}_W = \overline{\sigma}$, total welfare is maximized under full data sharing. Otherwise, partial data sharing or closed banking may be preferred.*

Recall that both $\hat{\sigma}_F$ and $\hat{\sigma}_W$ can lie in the interior of $[\underline{\sigma}, \overline{\sigma}]$ only if γ is sufficiently high. This leads to the following result:

Corollary 1. *If γ is sufficiently low, open banking (with full data sharing) is always welfare-enhancing; if γ is high, closed banking or open banking with partial data sharing might be socially optimal.*

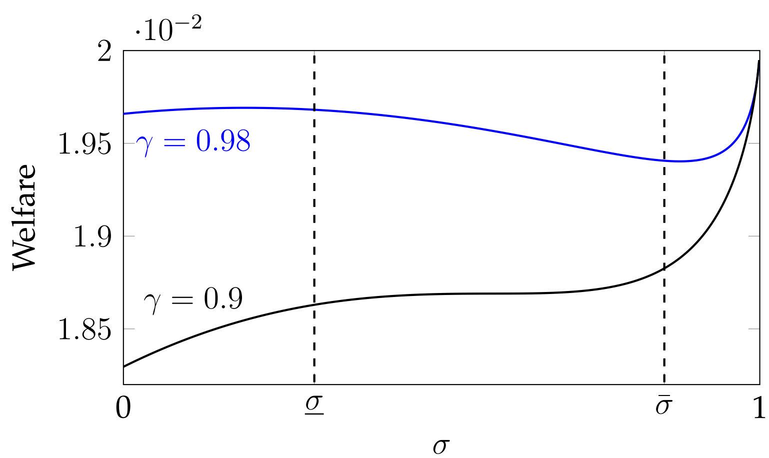


Figure 4: **Total Welfare as a function of the fintech's signal quality**. $Y = 2$, $\theta^H = 0.52$, $\theta^L = 0.48$, $\lambda = 0.5$, $\underline{\sigma} = 0.3$, $\bar{\sigma} = 0.85$

Figure 4 depicts different cases in which open banking may or may not be welfare-enhancing. For example, in **??**, γ is low and hence the total welfare is strictly increasing in the informativeness of the signal. In this case, open banking with full data sharing would be optimal. In Figure **??**, γ is high and hence total welfare is non-monotonic. In this case, open banking with full data sharing is not optimal. Partial data sharing is optimal but even closed banking dominates open banking.

This result allows us to derive important welfare implications regarding the effects of open banking. In particular, to the extent that γ reflects institutional characteristics—such as the level of economic development or the advancement and depth of a country's banking and financial systems—Proposition 3 implies that open banking is almost certainly welfare-enhancing in underdeveloped or emerging markets, where γ is likely to be low.[40] Empirical evidence supports this view. For instance, Frost et al. (2019) show that big tech credit is expanding rapidly in emerging markets with underdeveloped traditional banking sectors, leveraging alternative data to compensate for weak collateral systems. Similarly, Bazarbash (2019) documents that fintech credit is most transformative in markets where traditional credit registries are incomplete or where SMEs face severe credit constraints. Recent evidence by Carbó-Valverde et al. (2021) also highlights that open banking has more pronounced effects in countries with limited pre-existing credit infrastructure.

Even in advanced economies, open banking is more likely to yield positive welfare effects during the early stages of fintech diffusion and institutional learning—when digital infrastructure, credit scoring technologies, and data standardization mechanisms are still evolving, and the effective value of collateral (γ) remains relatively low due to market frictions or regulatory constraints.[41]

5.1.2 Property Rights and Data Markets

A common and important approach in economics is to compare the allocation of property rights among different participants and the creation of markets. For instance, the celebrated Coase Theorem (Coase 1960) establishes that when parties can bargain without frictions, they can not only reach mutually beneficial agreements but even agreements that are Pareto efficient. More importantly, and strikingly, Coase (1960) argues that the allocation of property rights affects only the distribution of surplus—not total welfare. Subsequent contributions challenged these conclusions. Among the most influential were those by Williamson (1985), Grossman and Hart (1986), and Hart and Moore (1990), who showed that when parties make non-contractible ex ante investments and lack commitment power, the allocation of property rights does matter. In such environments, owner-

[40]The value of collateral, γ, depends, apart from its physical or financial characteristics of the asset, on the institutional environment that governs enforcement. In underdeveloped economies, legal frictions, such as slow judicial processes, weak property rights, and high enforcement costs, significantly reduce the lender's ability to seize and liquidate collateral. As shown by Benmelech et al. (2024b), reductions in the enforceability of collateral—due to legal changes or institutional inefficiencies—lead to credit contraction and macroeconomic slowdowns, highlighting that collateral value is endogenous to the legal system.

[41]See Zetzsche et al. (2020b) for a legal and market design perspective on how open banking implementation in advanced economies often lags behind innovation due to underdeveloped data infrastructure and fragmented regulation. See also Campbell et al. (2021), who provides empirical evidence that the benefits of data-driven lending materialize gradually as institutions adapt and standardize digital credit systems.

ship determines incentives and affects both investment and welfare outcomes.

Open banking, as studied in the previous section, can be interpreted as allocating full property rights over data to one side of the market—namely, to the entrepreneurs. Under open banking, entrepreneurs control the data and may consent to its transfer to the fintech. In line with the incomplete contracts literature (Williamson, 1985, Grossman and Hart, 1986, and Hart and Moore, 1990) and assuming that contracts cannot specify ex ante how much data must be shared, Proposition 3 characterized the conditions under which full data sharing, partial data sharing, or closed banking is optimal for the different participants.

We now extend this reasoning by comparing different allocations of property rights. We consider two alternatives: (i) entrepreneurs own the rights (as under open banking), or (ii) one of the two lenders owns them. If entrepreneurs own the data, then—under the no-commitment assumption—the result mirrors open banking: they will voluntarily share all data with the fintech.[42]

An alternative is to assign property rights to one of the lenders. In this case, suppose that there exists a market for data, similar to that envisioned in Laudon (1996) and elaborated by more recent studies.[43] To keep the model tractable, we assume that the two lenders can negotiate over data usage in a way that maximizes their joint profits. When either lender owns the data, they will agree on the level of informativeness that maximizes their total surplus. Formally, the chosen signal is given by:

$$\hat{\sigma}_{BF} \in \underset{\sigma \in [\underline{\sigma}, \overline{\sigma}]}{arg\,max}\ \Pi_B(\sigma) + \Pi_F(\sigma). \tag{6}$$

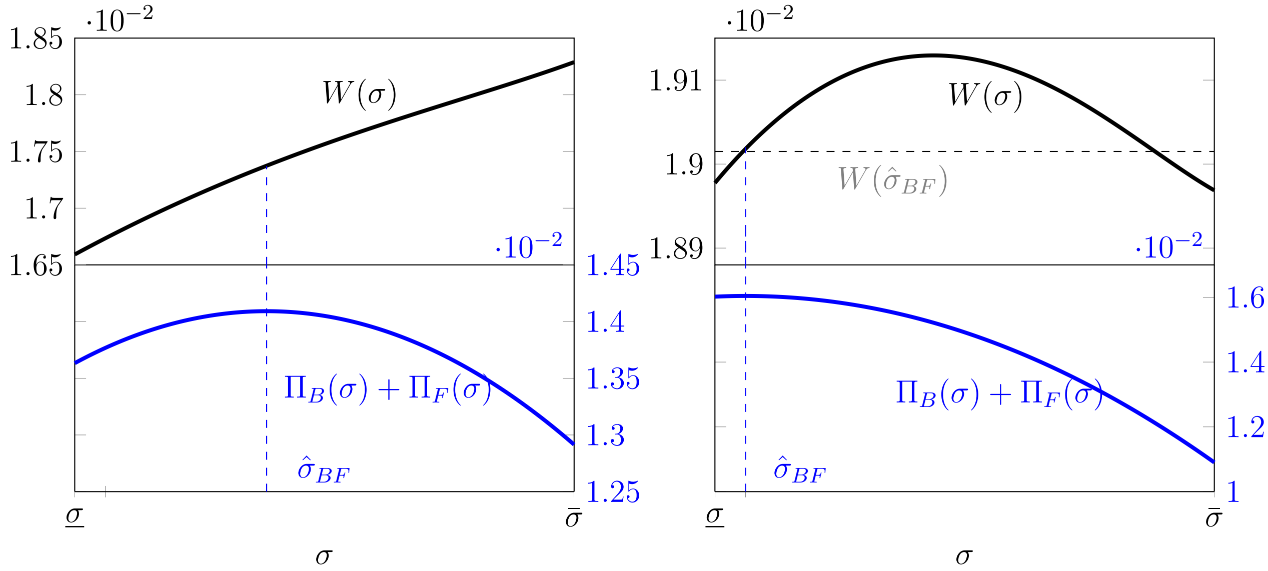
Recall that $\Pi_B(\sigma)$ is strictly decreasing σ whilst $\Pi_F(\sigma)$ is either strictly increasing for low γ and inverse U-shaped for high γ, the sum of the two profits can be either strictly increasing for low γ or inverse U-shaped for high γ as exemplified in Figure 4

The following lemma provides a full characterization of the maximizer of the joint profit.

Lemma 1. *There exists $\gamma_{BF} < \min\{\gamma_F, \gamma_W\}$ such that*

[42] This remains true even if there exists a market for data. So long as the data increase both the entrepreneurs' and the fintech's payoffs, a mutually beneficial transaction will take place. A price for data will be negotiated such that the fintech gains access to the full dataset.

[43] A growing literature explores the idea of data as a tradable asset and the institutional design of data markets. Laudon (1996) proposes formal markets where individuals can sell their personal information under clearly defined property rights. Varian (1997) analyzes the economic characteristics of information goods, including pricing strategies and licensing. Acquisti et al. (2016) surveys the economics of privacy, emphasizing trade-offs between efficiency, disclosure, and regulation. Spiekermann et al. (2015) examines the ethical and institutional challenges of personal data markets.



(a) $\gamma_{BF} < \gamma < \gamma_W$ (b) $\gamma < \gamma_W < \gamma_{BF}$

Figure 5: **Welfare and joint profit as a function of fintech's signal**. (a) $Y = 2$, $\theta^H = 0.52$, $\theta^L = 0.48$, $\lambda = 0.5$, $\gamma = 0.8$, $[\underline{\sigma}, \bar{\sigma}] = [0, 0.7]$. (b) $Y = 2$, $\theta^H = 0.55$, $\theta^L = 0.45$, $\lambda = 0.5$, $\gamma = 0.94$, $\bar{\sigma}] = [0, 0.7]$.

1. *For* $\gamma \leq \gamma_{BF}$*,* $\Pi_B(\sigma) + \Pi_F(\sigma)$ *is strictly increasing in* σ*.*

2. *For* $\gamma > \gamma_{BF}$*,* $\Pi_B(\sigma) + \Pi_F(\sigma)$*, inverse U-shaped in* σ*.*

We can now, based on Lemma 1, characterize the optimal allocation of property rights. In particular, when γ is sufficiently low, the resulting outcome is identical under any allocation of property rights; hence, the specific allocation is irrelevant for welfare. This equivalence, however, breaks down when γ is high. In that case, it is possible to have $\hat{\sigma}_{BF} < \overline{\sigma}$ in which case the allocation of property rights matters and can have significant implications. A full characterization is summarized in the following proposition.

Proposition 4 (Optimal Allocation of Property Rights)**.** *Suppose there is a functioning market for data. The optimal allocation of property rights depends critically on the informativeness of the signal and the value of collateral:*

1. *If* $\gamma \leq \gamma_{BF}$*, the allocation of property rights is irrelevant for welfare. In this case, open banking leads to the same outcome as assigning property rights to either of the two lenders.*

2. *If* $\gamma_{BF} < \gamma < \gamma_W$*, the allocation of property rights is either irrelevant or open banking is strictly preferable. In particular, when* $\hat{\sigma}_{BF} < \overline{\sigma}$*, open banking yields strictly higher welfare than any allocation where a lender owns the rights.*

3. *If $\gamma \geq \gamma_W$, the optimal allocation of property rights is context-specific. If $W(\hat{\sigma}_{BF}) < W(\hat{\sigma}_W)$, open banking maximizes social welfare; otherwise, either the allocation of property rights is irrelevant, or allocating property rights to a lender yields superior outcomes.*

Recall that due to limited commitment, the allocation of property rights becomes welfare-relevant. When entrepreneurs own the rights, they are willing to sell all their data to the fintech, knowing this improves their welfare.[44] On the other hand, when one of the lenders owns the rights, data sharing can be fine-tuned through negotiation. Specifically, the bank—preferring no data transfer without compensation—and the fintech—wishing to acquire at least some data—have opposing preferences. A mutually beneficial agreement can therefore emerge, maximizing joint profits and leading to surplus-sharing. In this sense, assigning data ownership to one of the lenders serves as a partial commitment device, limiting σ and potentially improving welfare by constraining over-sharing.

In line with the previous analysis, Proposition 4 implies important policy conclusions regarding the optimal institutional design. Conditional on the existence of a data market, the allocation of property rights is irrelevant for social welfare when γ is low. For intermediate γ, either the allocation of property rights is irrelevant or open banking is strictly preferable. This suggests that in environments with relatively low γ—such as underdeveloped or emerging economies—open banking may indeed be the welfare-maximizing institutional choice.

By contrast, when γ is high, open banking is not necessarily optimal. In such cases, it may be dominated by institutional frameworks in which data property rights are assigned to lenders, along with access to a well-structured market. These insights carry important policy implications for advanced economies, where high collateral value and institutional sophistication may call for more nuanced data governance models.

Note that several real-world initiatives aim to institutionalize data sharing through structured markets and alternative governance models. For instance, *Ocean Protocol* is a decentralized platform that facilitates secure and privacy-preserving data sharing using blockchain technology and data tokens, allowing individuals or institutions to retain control while monetizing access. *Dawex* operates a global data marketplace where organizations can buy, sell, or exchange data under transparent licensing terms. Another emerging approach is that of *data unions*—collective organizations that enable individuals to pool their data and negotiate its use collectively. These models provide promising alternatives to traditional open banking by aligning data ownership, privacy, and economic

[44] As discussed earlier, in the absence of commitment, the fintech will ultimately acquire all the data. This makes the outcome under entrepreneur ownership equivalent to full open banking.

incentives. See also Delacroix and Lawrence (2021), Majeed et al. (2023), and Moser et al. (2021) for discussions on data governance and collective data rights.

5.2 Improvements in Data Analytics and Predictions

Our framework also sheds light on the incentives of lenders—particularly fintechs—to invest in acquiring and processing information. Recent empirical evidence confirms that fintech lenders enhance credit screening by leveraging alternative data sources. For example, Balyuk and Gurun (2023) shows that fintech platforms strategically invest in information acquisition, such as bank transaction and spending data, to better evaluate opaque borrowers and mitigate adverse selection.

From an economic perspective, it is important to compare the fintech's private incentives for information acquisition with what is socially optimal. In our model, this corresponds to comparing the fintech-optimal signal precision $\hat{\sigma}_F$–defined in equation (4)–with the socially optimal level $\hat{\sigma}_W$, as defined in equation (5). For simplicity, we assume that acquiring information is costless for the fintech.[45] The key question, then, is whether the fintech's privately optimal choice of σ aligns with the level that maximizes social welfare—highlighting potential distortions between private and public incentives for information acquisition in financial markets.

Recall that for $\gamma \leq \min\{\gamma_F, \gamma_W\}$, both the profit of the fintech and total welfare are strictly increasing in σ. In this case, the fintech would choose the highest possible level of informativeness (i.e., $\hat{\sigma}_F = \overline{\sigma}$), which also coincides with the socially optimal choice under a utilitarian planner maximizing total surplus. In other words, when γ is sufficiently low, the incentives of the fintech align with those of society.

For higher values of γ, several possibilities emerge. Suppose, for instance, that $\gamma_F < \gamma_W$ and $\gamma \in (\gamma_F, \gamma_W)$. In this case, $\hat{\sigma}_F$ may be interior while $\hat{\sigma}_W = \overline{\sigma}$, implying that the fintech underinvests relative to the social optimum. Conversely, if $\gamma_F > \gamma_W$ and $\gamma \in (\gamma_W, \gamma_F)$, the fintech overinvests. In short, when γ is sufficiently high, both over- and under-investment are likely depending on parameter values. This leads to the following result:

Proposition 5 (Improvements in Data Analytics)**.** *Suppose that the fintech can determine the informativeness of the signal through investment in data analytics and/or information processing.*

1. *For $\gamma \leq \min\{\gamma_F, \gamma_W\}$, the fintech's incentives align with those of society.*

[45] Introducing a convex cost $\psi(\sigma)$ would not alter the qualitative conclusions: since $\Pi_F(\sigma)$ is either strictly increasing or inverse U-shaped, the net payoff $\Pi_F(\sigma) - \psi(\sigma)$ remains concave, implying a unique interior optimum.

2. *For $\gamma > \min\{\gamma_F, \gamma_W\}$, misalignment arises, and both over- and under-investment are possible.*

Proposition 5 highlights the role of non-internalized externalities. The fintech's investment decision affects all other participants in the market (i.e., borrowers and the bank). When γ is low, both the fintech and society have strong incentives to increase σ to avoid the cost of collateralization, resulting in aligned objectives. When γ is high, however, this alignment breaks down-leading to either excessive or insufficient investment in data analytics.

These insights yield important policy implications. When γ is low, such as in emerging markets with weak collateral enforcement or high formalization costs, fintechs already have strong private incentives to invest in superior data analytics, and regulatory intervention may be unnecessary or even distortive. By contrast, when γ is high—as is often the case in advanced economies with deep collateral markets and efficient judicial enforcement—private incentives may not be aligned with those of a social planner. In such contexts, fintechs may either overinvest in data analytics to gain a competitive advantage or underinvest if excessive precision reduces profitability. This divergence justifies targeted policy tools such as investment tax credits, data-access subsidies, or regulation of predictive technologies to align private incentives with social welfare. For example, the European Commission's Digital Finance Package explicitly supports open data access and ethical AI in credit scoring, precisely to manage this trade-off between innovation and inclusion.[46]

6 Conclusion

We study competition in a loan market with adverse selection between a bank and a fintech that are asymmetric along two key dimensions: their ability to screen borrowers and their capacity to extract value from collateralized assets in case of default. Open banking and improvements in data analytics—by increasing the precision of the fintech's signal—strengthen the fintech's competitive position, reduce adverse selection, and allow for the provision of more unsecured loans. However, they also intensify competition, compelling the bank to respond with more aggressive (i.e., higher collateral) offers. This trade-off lies at the heart of our analysis.

Our main contribution is to show that improvements in information are not always welfare-enhancing. While they reduce the inefficiencies associated with collateralization,

[46]See European Commission (2020), *Digital Finance Strategy for the EU*, COM(2020)591. Available at: https://finance.ec.europa.eu/system/files/2020-09/200924-digital-finance-strategy_en.pdf.

they can also induce destructive competition and over-collateralization. As a result, the relationship between the informativeness of the fintech's signal and social welfare is non-monotonic. We establish conditions under which open banking enhances borrower surplus but reduces total welfare, and even cases where it is detrimental to fintechs themselves.

Despite the simplicity of our model, this trade-off persists in more general environments. Allowing the bank to also identify some borrowers would not overturn the result; it would lead the bank to offer unsecured loans to those it can identify, and the key distortion would still arise in the contested region where types are uncertain. Similarly, generalizing the signal structure to allow for false positives and false negatives introduces new sources of inefficiency, potentially strengthening our result. In particular, over-optimistic assessments by fintechs may lead to credit misallocation and higher default, reinforcing the non-monotonicity between information and welfare.

We also examine alternative institutional arrangements for data sharing, such as assigning property rights over data and establishing data markets. Our analysis shows that these alternatives can, in some cases, dominate open banking. For example, when the bank's comparative advantage in enforcing collateral is strong and the fintech's informational advantage is moderate, a regime where data is traded or controlled by lenders can outperform full data portability. These results resonate with recent discussions on markets for personal data and property rights over digital information.

From a policy perspective, our findings suggest that granting borrowers full control over their financial data—as in open banking regimes—does not guarantee welfare improvements. In environments where the costs of collateralization are high or legal institutions are weak, open banking may be beneficial. But in well-developed financial systems with strong lender protections, unrestricted data sharing may actually reduce market efficiency. In such contexts, partial or regulated access to data, as well as institutional mechanisms that restrict the flow or usage of information, may improve outcomes. In this sense, our model calls for a more nuanced approach to data governance in credit markets—one that balances competition, information, and collateral constraints.

Our results are broadly consistent with a number of recent empirical studies (Babina et al. 2025; Nam 2022; Fuster et al. 2019b; Balyuk and Gurun 2023; and Benmelech et al. 2024a, among others).

References

ACQUISTI, A., C. TAYLOR, AND L. WAGMAN (2016): "The Economics of Privacy," *Journal of Economic Literature*, 54, 442–492.

BABINA, T., S. A. BAHAJ, G. BUCHAK, F. DE MARCO, A. K. FOULIS, W. GORNALL, F. MAZZOLA, AND T. YU (2025): "Customer Data Access and Fintech Entry: Early Evidence from Open Banking," *Journal of Financial Economics*, 169, 104100.

BALYUK, T. AND U. G. GURUN (2023): "FinTech Lending and Information Acquisition," *Journal of Financial Economics*, 148, 453–475.

BAZARBASH, M. (2019): "Fintech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk," IMF Working Paper WP/19/109, International Monetary Fund.

BENMELECH, E., K. KUMAR, AND R. RAJAN (2024a): "Collateral Reductions and Macroeconomic Outcomes," *Journal of Finance*, forthcoming.

BENMELECH, E., N. KUMAR, AND R. RAJAN (2024b): "The Benefits and Costs of Secured Debt," NBER Working Paper No. 32353.

BERG, T., V. BURG, A. GOMBOVIĆ, AND M. PURI (2020): "On the Rise of FinTechs: Credit Scoring Using Digital Footprints," *Journal of Finance*, 75, 2451–2493.

BERGEMANN, D., A. BONATTI, AND A. SMOLIN (2019): "Markets for information: An introduction," *Annual Review of Economics*, 11, 85–107.

BERGER, A. N. AND G. F. UDELL (1990): "Collateral, Loan Quality, and Bank Risk," *Journal of Monetary Economics*, 25, 21–42.

BESTER, H. (1985): "Screening vs. Rationing in Credit Markets with Imperfect Information," *The American Economic Review*, 75, 850–855.

——— (1987): "The role of collateral in credit markets with imperfect information," *European Economic Review*, 31, 887–899.

BLUME, A. (2003): "Bertrand without fudge," *Economics Letters*, 78, 167–168.

BOOT, A. W. A., A. V. THAKOR, AND G. F. UDELL (1991): "Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results," *The Economic Journal*, 101, 458–472.

CAMPBELL, J. Y., P. GOLDSMITH-PINKHAM, F. WANG, AND A. YANG (2021): "Banking on data: Big data and the future of the financial industry," *Brookings Papers on Economic Activity*, 2021, 233–288.

CARBÓ-VALVERDE, S., P. CUADROS-SOLAS, AND F. RODRÍGUEZ-FERNÁNDEZ (2021): "Open Banking and Financial Inclusion: Evidence from the UK," *Finance Research Letters*, 38, 101444.

CARR, M. AND A. THAKOR (2023): "Regulated access to consumer data: Designing data governance for open finance," *Journal of Financial Regulation and Compliance*, 31, 48–66.

CARULLO, G. (2021): "Open banking, access to data, and the role of APIs: Lessons from the EU Payment Services Directive," *Computer Law Security Review*, 41, 105530.

CERQUEIRO, G., S. ONGENA, AND K. ROSZBACH (2020): "Collateral damaged? Priority structure, credit supply, and firm performance," *Journal of Financial Intermediation*, 44, 100824.

COASE, R. H. (1960): "The Problem of Social Cost," *Journal of Law and Economics*, 3, 1–44.

DE MEZA, D. AND D. C. WEBB (1987): "Too much investment: A problem of asymmetric information," *The Quarterly Journal of Economics*, 102, 281–292.

DELACROIX, S. AND N. LAWRENCE (2021): "Data unions: Collective data rights and the rise of data cooperatives," *Philosophy & Technology*, 34, 1–25.

DJANKOV, S., O. HART, C. MCLIESH, AND A. SHLEIFER (2008): "Debt Enforcement around the World," *Journal of Political Economy*, 116, 1105–1149.

DOSIS, A. AND W. SAND-ZANTMAN (2024): "The Ownership of Data," *Journal of Law, Economics, & Organization*, 40, 364–402.

ELYASIANI, E. AND L. G. GOLDBERG (2004): "Relationship lending: a survey of the literature," *Journal of Economics and Business*, 56, 315–330, research Perspectives Special Issue.

FROST, J., L. GAMBACORTA, Y. HUANG, H. S. SHIN, AND P. ZBINDEN (2019): "BigTech and the Changing Structure of Financial Intermediation," *Economic Policy*, 34, 761–799.

FUSTER, A., P. GOLDSMITH-PINKHAM, T. RAMADORAI, AND A. WALTHER (2019a): "Predictably Unequal? The Effects of Machine Learning on Credit Markets," Staff Report 940, Federal Reserve Bank of New York.

FUSTER, A., M. C. PLOSSER, P. SCHNABL, AND J. I. VICKERY (2019b): "The Role of Technology in Mortgage Lending," *Review of Financial Studies*, 32, 1854–1899.

GAMBACORTA, L., Y. HUANG, Z. LI, H. QIU, AND S. CHEN (2022): "Data versus Collateral*," *Review of Finance*, 27, 369–398.

GIGLIO, F. ET AL. (2021): "Fintech: A literature review," *European Research Studies Journal*, 24, 600–627.

GIORGIO, B. N., G. CALZOLAR., M.-F. JOSÉ, AND P. A. FRANCO (2018): "Fintech and Banking. Friends or Foes?" *SSRN Electronic Journal*.

GOPAL, M. AND P. SCHNABL (2022): "The rise of finance companies and fintech lenders in small business lending," *The Review of Financial Studies*, 35, 4859–4901.

GRECK, B., M. GREGOR, P. TOMASZ, AND S. AMIT (2018): "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 130, 453–483.

GROSSMAN, S. J. AND O. D. HART (1986): "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration," *Journal of Political Economy*, 94, 691–719.

GUPTA, A., T. HANSPAL, AND R. TOWNSEND (2023): "Real Estate and Small Business Lending: Evidence from Bank Loans," *Review of Financial Studies*, forthcoming.

HART, O. AND J. MOORE (1990): "Property Rights and the Nature of the Firm," *Journal of Political Economy*, 98, 1119–1158.

HE, Z., J. HUANG, AND J. ZHOU (2023): "Open banking: Credit market competition when borrowers own the data," *Journal of Financial Economics*, 147, 449–474.

ICHIHASHI, S. (2020): "The economics of data: Implications for the data-driven economy," *American Economic Journal: Microeconomics*, 12, 1–44.

JENTZSCH, N. (2019): "Data governance and data markets: What role for the state?" *Internet Policy Review*, 8, 1–18.

JING, H. (2021): "Fintech expansion," *Available at SSRN 3957688*.

JONES, C. I. AND C. TONETTI (2020): "Nonrivalry and the Economics of Data," *American Economic Review*, 110, 2819–2858.

LAUDON, K. C. (1996): "Markets and Privacy," *Communications of the ACM*, 39, 92–104.

MAJEED, S., U. SIVARAJAH, AND V. WEERAKKODY (2023): “Data markets and the future of digital governance,” *Government Information Quarterly*, 40, 101750.

MANOVE, M., A. J. PADILLA, AND M. PAGANO (2001): “Collateral versus Project Screening: A Model of Lazy Banks,” *The RAND Journal of Economics*, 32, 726–744.

MOSER, C., A. GRAN, AND M. SAX (2021): “Data Unions in the Platform Economy: Opportunities and Limitations,” *Internet Policy Review*, 10.

NAM, R. J. (2022): “Open Banking and Customer Data Sharing: Implications for FinTech Borrowers,” Latest version: October 2023; empirical evidence from a large German FinTech lender.

PAGANO, M. AND T. JAPPELLI (1993): “Information Sharing in Credit Markets,” *American Economic Review*, 83, 1693–1708.

PARLOUR, C. A., U. RAJAN, AND H. ZHU (2022): “When FinTech Competes for Payment Flows,” *The Review of Financial Studies*, 35, 4985–5024.

PETERSEN, M. A. AND R. G. RAJAN (1994): “The Benefits of Lending Relationships: Evidence from Small Business Data,” *Quarterly Journal of Economics*, 109, 3–37.

POZZOLO, A. F. (2002): “The Role of Guarantees in Bank Lending,” *Journal of Banking & Finance*, 26, 915–939.

ROTHSCHILD, M. AND J. E. STIGLITZ (1976): “Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information,” *The Quarterly Journal of Economics*, 90, 629–649.

SERFES, K., K. WU, AND P. AVRAMIDIS (2025): “FinTech vs. Bank: The impact of lending technology on credit market competition,” *Journal of Banking & Finance*, 170, 107338.

SPIEKERMANN, S., A. ACQUISTI, R. BÖHME, AND K.-L. HUI (2015): “The Challenges of Personal Data Markets and Privacy,” *Electronic Markets*, 25, 161–167.

STIGLITZ, J. E. AND A. WEISS (1981): “Credit Rationing in Markets with Imperfect Information,” *The American Economic Review*, 71, 393–410.

VARIAN, H. R. (1980): “A Model of Sales,” *American Economic Review*, 70, 651–659.

——— (1997): “Markets for Information Goods,” *California Management Review*, 39, 38–55.

VIVES, X. AND Z. YE (2023): "Information Technology and Bank Competition," *SSRN Electronic Journal*.

WILLIAMSON, O. E. (1985): *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*, New York: Free Press.

ZETZSCHE, D. A., R. P. BUCKLEY, D. W. ARNER, AND J. N. BARBERIS (2020a): "The access condition in data regulation: A European perspective on open finance," *Journal of Banking Regulation*, 21, 115–125.

——— (2020b): "Open Banking, Open Finance, and Open Data: The Promise and Limits of Data Sharing in Financial Services," *Fordham Journal of Corporate & Financial Law*, 25, 1–61.

A Appendix

A.1 Notation

Payoffs and specific contracts.

- We denote any contract (R, C) by x. Lenders' per-borrower profit from any such contract with type i borrower is denoted by: $\pi^i_\zeta(x)$, and type i borrower's incremental utility from such contract is denoted by: $u^i(x) = \theta^i(Y - R) - (1 - \theta^i)C$. We further ease the notation by using $u(x) = u^H(x)$.

- We denote the indifference curve of low-type borrowers where they have zero profit as $IC^0 = \{x \mid u^L(x) = 0\}$. This line partitions the contract space in three regions: the contracts on the line; the contracts on the right side of the line which are denoted by $IC^- = \{x \mid u^L(x) < 0\}$; and the contracts on the left side of the line denoted by $IC^+ = \{x \mid u^L(x) > 0\}$.

- Per-borrower welfare of a contract x between borrower i and lender ζ is denoted as $w^i(x)$. It is straightforward that, for contracts with no collateral $x = (R, 0)$, accepted by a high-type borrower, we have:

$$w^H(x) = \theta^H Y - 1 - r_0 \equiv \bar{w}$$

  The per-borrower profit of the lenders from such a contract with no collateral with a high-type borrower then writes $\pi^H_\zeta(x) = \bar{w} - u(x)$.

- For contracts x_{IC^0} on the IC^0 line, we have $Y - R = \frac{1-\theta^L}{\theta^L}C$. The utility of the high-type borrower from such contract then writes:

$$u(x_{IC^0}) = \theta^h \frac{1 - \theta^L}{\theta^L} C - (1 - \theta^H)C = C\frac{\theta^H - \theta^L}{\theta^L}.$$

  The welfare of a contract on the IC^0 line between lender ζ and a borrower of high type then writes:

$$w(x_{IC^0}) = \bar{w} - (1 - \theta^H)(1 - \gamma_\zeta)C = \bar{w} - u(x_{IC})\frac{(1 - \theta^H)(1 - \gamma_\zeta)\theta^L}{\theta^H - \theta^L}.$$

  We denote:

$$\beta^\zeta \equiv \frac{(1 - \theta^H)(1 - \gamma_\zeta)\theta^L}{\theta^H - \theta^L}.$$

  We can then write $w(x_{IC^0}) = \bar{w} - \beta^\zeta u(x_{IC})$, and $\pi^i(x_{IC^0}) = \bar{w} - (1 + \beta)u(x_{IC})$.

  We can further simplify the notation by denoting $\beta = \beta^\zeta$.

- We define the function $G(.)$ such that it maps contracts on the IC^0 line to contracts with no collateral such that the hight-type borrower is indifferent between them. Formally:

$$G : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \text{ s.t if } x' = (R, 0) = G(x_{IC^0}), \text{ then } u(R, 0) = u(x_{IC^0}).$$

- We denote the contract on the IC^0 line for which the fintech earns zero profit when the high-type borrower accepts it by x_0^-. Formally x_0^- is such that $u^L(x_0^-) = 0$ and $\pi_F^H(x_0^-) = 0$. Then:
$$x_0^- = (\frac{1 + r_0}{\theta^H}, \frac{\bar{w}\theta^L}{\theta^H(1 - \theta^L)}).$$
We denote contract x_1^- on the IC^0 line such that $\pi_B^H(x_1^-) = (1 - \sigma)\pi_B^H(x_0^-)$. Note that since $\gamma_B > \gamma_F = 0$, this contract exists and $\pi_B^H(x_1^-) > 0$ for $\sigma \neq 1$.

Strategies and Equilibrium. We denote lenders' strategies as $X_\zeta = (X_\zeta^+, X_\zeta^-)$, where X_ζ^+ is the loan contract offered by lender ζ to borrowers who have a positive signal from lender ζ, and X_ζ^- is the loan contract offered by lender ζ to borrowers who have a bad signal from lender ζ.

We denote a pure strategy of lender ζ as (x_ζ^+, x_ζ^-). We define a mixed strategy of lender ζ as a pair $(f_\zeta(.), M_\zeta)$, which is a joint probability density function $f_\zeta(x^+, x^-) > 0$ over a non-empty set $M = M^+ \times M^-$, such that for any $A \subset M$:

$$\mathbb{P}\{(x_\zeta^+, x_\zeta^-) \in A\} = \iint\limits_A f_\zeta(x^+, x^-).dx^+.dx^-.$$

Hence, when a lender plays a mixed strategy, he offers contract x_ζ^+ to borrowers with a positive signal and contract x_ζ^- to borrowers with a negative signal such that (x_ζ^+, x_ζ^-) is a random draw of $f_\zeta(.)$ over the support M_ζ [47].

We denote the marginal probability distribution functions of $(f_\zeta(.), M_\zeta)$ as follows:

$$f_\zeta^+(x^+, \dot{x}^-) = \mathbb{P}\{(x_\zeta^+, \dot{x}_\zeta^-) \in A\} = \int\limits_A f_\zeta(x_\zeta^+, \dot{x}_\zeta^-).dx^+, \;\; \forall \dot{x}_\zeta^- \in M_\zeta^-, \text{ and } A \subset M.$$

$$f_\zeta^-(\dot{x}^+, x^-) = \mathbb{P}\{(\dot{x}_\zeta^+, x_\zeta^-) \in A\} = \int\limits_A f_\zeta(\dot{x}_\zeta^+, x_\zeta^-).dx^-, \;\; \forall \dot{x}_\zeta^+ \in M_\zeta^+, \text{ and } A \subset M.$$

We denote borrowers' strategy by $D^i = (d_B^i, d_F^i)$ such that $d_\zeta^i \in [0, 1]$ is the probability that a borrower of type i accepts the contract offered by lender ζ, and $d_B^i + d_F^i \in [0, 1]$.

[47]We impose that $f_\zeta(x^+, x^-)$ assigns a non-zero density to any contract in M_ζ.

We then denote the profit of lender ζ as $\Pi_\zeta(X_\zeta, X_{\zeta'}, D^i) = \Pi_\zeta^+(X_\zeta, X_{\zeta'}, D^i) + \Pi_\zeta^-(X_\zeta, X_{\zeta'}, D^i)$, where $\Pi_\zeta^+(X_\zeta, X_{\zeta'}, D^i)$ denotes the profit from offers to borrowers with a positive signal, and $\Pi_\zeta^-(X_\zeta, X_{\zeta'}, D^i)$ denotes the profit from offers to borrowers with a negative signal, when the other lender plays $X_{\zeta'}$ and borrowers choice of contract is D^i.

A PBE is denoted by $\hat{E} = (\hat{X}_B, \hat{X}_F, \hat{D}^h, \hat{D}^b)$ such that:

$$\hat{X}_\zeta = \operatorname{argmax}\{\Pi_\zeta(X_\zeta, X_{\zeta'}, D^i(X_\zeta, X_{\zeta'}))\},$$

$$\hat{D}^i(X_B, X_F) = \operatorname{argmax}\{d_B^i u^i(X_B^i) + d_F^i u^i(X_F^i)\}.$$

A.2 Omitted Proofs

Proof. of Proposition 1:

We characterize the unique class of equilibria in undominated strategies by a series of claims:

Claim 1. *In equilibrium, contracts accepted by borrowers must either have no collateral or lie on the IC^0 line.*

Proof of claim 1:

a) Consider contracts offered by a lender to borrowers for whom the lender has a negative signal, x_ζ^-. First assume that $x_\zeta^- \in IC^-$. Since IC^0 line is steeper than the iso-profit of the lenders for offers to good-type borrowers (ZP_ζ^H), there exist a contract x'_{IC} such that $u(x'_{IC^0}) = u(x_\zeta^-)$ and $\pi^h(x'_{IC^0}) > \pi^h(x_\zeta^-)$. This implies that, if contract $x_\zeta^- \in IC^-$ is accepted by high-type borrowers with a positive probability, the lender has a profitable deviation by offering x'_{IC} instead.

   Next, assume that $x_\zeta^- \in IC^+$. Two cases are possible. First, if the other lender's offer to borrowers with negative signal lies on the IC^0 line or to its right-side, all low-type borrowers accept x_ζ^-. By assumption $\frac{r}{\theta^H} < Y < \frac{r}{\theta^\circ}$, lender ζ yields negative profit from this offer and hence has a profitable deviation by offering no contract. Next, if the other lender's offer to borrowers with negative signal is also on the left-side of IC^0 line, all low-type borrowers accept one of these offers. In that case, by assumption $\frac{r}{\theta^H} < Y < \frac{r}{\theta^\circ}$, the sum of lenders' profits from these offers must be negative, implying that at least one lender has a profitable deviation by offering no contract.

b) Consider contracts offered by a lender to borrowers for whom the lender has a positive signal, $x_\zeta^+ = (R, C)$. Assume that $C > 0$. Since a positive signal ensures that the borrower is of high type, there exist a contract $x' = (R, 0)$ such that such that $u(x') = u(x_\zeta^+)$ and $\pi^h(x') > \pi^h(x_\zeta^+)$. Hence, if this contract is accepted by good-type borrowers with a positive probability, the lender has a profitable deviation by offering $x' = (R, 0)$ instead.

Following claim 1, we characterize the equilibrium in which only contracts on the IC^0 line or contracts with no collateral are offered. Therefore, here on, $X^- \in IC^0$, and $X^+ = (R, 0)$.

Since, in these sets of contracts, the utility of high-type borrower from any contract is unique, we can specify each contract by the utility that the high-type borrower derives from accepting it. We can write the marginal probability distribution functions of $f_\zeta(.)$ on M_ζ as[48]:

$$f_\zeta^+(u(x^+), \dot{x}^-) = \int\limits_A f_\zeta(u(x_\zeta^+), \dot{x}_\zeta^-).du(x^+), \ \ \forall \dot{x}_\zeta^- \in M_\zeta^-, \ \text{ and } \ A \subset M.$$

$$f_\zeta^-(\dot{x}^+, u(x^-)) = \int\limits_A f_\zeta(\dot{x}_\zeta^+, u(x_\zeta^-)).du(x^-), \ \ \forall \dot{x}_\zeta^+ \in M_\zeta^+, \ \text{ and } \ A \subset M.$$

Claim 2. *There exist no pure strategy equilibrium.*

Proof of claim 2: Assume fintech offers $X_F = (x_F^+, x_F^-)$ in pure strategy.

a) Assume $u(x_F^+) > u(x_F^-)$. Bank's profit form any offer x_B writes:

$$\Pi_B(x_B, X_F) = \begin{cases} 0 & , \ u(x_B) < u(x_F^-) \\ \frac{1}{2}(1-\sigma)\pi_B^H(x_B) & , \ u(x_B) = u(x_F^-) \\ (1-\sigma)\pi_B^H(x_B) & , \ u(x_F^+) < u(x_B) < u(x_F^+) \\ (1-\frac{\sigma}{2})\pi_B^H(x_B) & , \ u(x_B) = u(x_F^+) \\ \pi_B^H(x_B) & , \ u(x_B) > u(x_F^-) \end{cases}$$

[48]Consequently, we can define the corresponding cumulative distribution functions as follows:

$$\forall x, \dot{x} \in M_B, \ \ F_B(\dot{x}) = \mathbb{P}\{u(x) \le u(\dot{x})\} = \int\limits_{u(x_0^-)}^{u(\dot{x})} f_B(u(x)).du(x),$$

$$\forall x^+, \dot{x}^+ \in M_F^+, \ \ F_F^+(\dot{x}^+, \dot{x}^-) = \mathbb{P}\{u(x^+) \le u(\dot{x}^+)\} = \int\limits_{u(x_0^-)}^{u(\dot{x}^+)} f_F^+(u(x^+), \dot{x}^-).du(x^+), \ \ \dot{x}^- \in M_F^-$$

$$\forall x^-, \dot{x}^- \in M_F^-, \ \ F_F^-(\dot{x}^+, \dot{x}^-) = \mathbb{P}\{u(x^-) \le u(\dot{x}^-)\} = \int\limits_{u(\underline{x}^-)}^{u(\dot{x}^-)} f_F^-(\dot{x}^+, u(x^-)).du(x^-), \ \ \dot{x}^+ \in M_F^-$$

First, note that, if there exist any contract x such that $u(x) \geq u(x_F^-)$ and $\pi_B^H(x) > 0$, the bank's profit $\Pi_B(x_B, X_F)$ is discontinuous. It is straightforward that the discontinuity of bank's profit implies that no contract x_B can construct an equilibrium. Next, note that, if $\pi_B^H(x) \leq 0$ for any x such that $u(x) \geq u(x_F^-)$, the assumption $\gamma_B > \gamma_F$ implies that fintech earns negative profit from the offer x_F^- and hence for any x_B has a profitable deviation.

b) Similarly, for cases where $u(x_F^+) \leq u(x_F^-)$, bank's profit would be discontinuous and no contract x_B can construct an equilibrium.

Claim 3. *Offering any contract x^- such that $\pi_\zeta^L(x^-) < 0$ is a weakly dominated strategy for the fintech.*

Proof of claim 3: Lender ζ has either negative profit from offering x^- such that $\pi_\zeta^H(x^-) < 0$, if it is accepted by any borrower, or zero profit if it is not accepted by any borrower. Any contract x' on the IC^0 line such that $\pi_\zeta^H(x') > 0$ yields either positive or zero profit, and therefore weakly dominates contracts x^- such that $\pi_\zeta^H(x^-) < 0$.

Claim 4. *In a mixed strategy equilibrium, we must have:*

$$\text{Sup}\{u(x) \mid x \in M_F^-\} < \text{Inf}\{u(x) \mid x \in M_F^+\}$$

Proof of claim 4: In a mixed strategy equilibrium, fintech must be indifferent among all contracts in M_F^+:

$$\Pi_F^+(x_F^+, X_B) = \lambda\sigma F_B(u(x^+))\pi_F^H(x^+) = k, \ \ \forall x_F^+ \in M_F^+,$$

for some $k \geq 0$. First assume $k = 0$. Consider contract x_{0B}^- such that $\pi_B^H(x_{0B}^-) = 0$. Then, for $\gamma_B < 1$, fintech can offer a contract x^+ such that $u(x^+) > u(x_{0B}^-)$ and have a positive profit by attracting all high-type borrowers[49] Hence, we must have $k > 0$, and

$$F_B(u(x^+)) = \frac{k}{\lambda\sigma\pi_F^H(x^+)} = \frac{k}{\lambda\sigma(\bar{w} - u(x_F^+))}, \ \ \forall x_F^+ \in M_F^+$$

Then, for any contract x^- such that $u(x^-) \in \{u(x) \mid x \in M_F^+\}$, fintech's profit writes:

$$\Pi_F^-(x_F^-, X_B) = \lambda(1-\sigma)F_B(u(x_F^-))\pi^H(x_F^-) = \frac{k(1-\sigma)(\bar{w} - (1+\beta^F)u(x_F^-))}{\lambda\sigma(\bar{w} - u(x_F^-))},$$

which is strictly decreasing in $u(x_F^-)$, since $\beta^F > 0$. Hence, fintech can not be indifferent among contracts x^- such that $u(x^-) \in \{u(x) \mid x \in M_F^+\}$. In fact, if fintech is indifferent

[49] If such a contract does not attract any high-type borrower, then the bank must be offering some contract x such that $u(x) > u(x_{0B}^-)$, accepted by all high-type borrowers. In that case, the bank earns negative profit from such offers and therefore has a profitable deviation.

among contracts in M_F^+, he strictly prefer to offer contracts x_F^- such that $u(x_F^-) \leq \text{Inf}\{u(x) \mid x \in M_F^+\}$. This implies that, in equilibrium, the fintech's offer to borrowers with a positive signal must yield a higher utility for high-type borrowers than his offers to borrowers with a negative signal.

Claim 5. *In a mixed strategy equilibrium in undominated strategies, fintech has zero profit from his offers to borrowers with negative signal:* $\Pi_F^-(\hat{E}) = 0$.

Proof of claim 5: Assume that $\Pi_F^-(\hat{E}) > 0$. Then there should exist $\dot{x}^-$ offered by the fintech such that $\pi_F^H(\dot{x}^-) > 0$, and

$$\lambda(1-\sigma)F_B(u(\dot{x}^-))\pi_F^H(\dot{x}^-) > 0.$$

This implies that $F_B(\dot{x}^-) > 0$ for some $\dot{x}^-$ such that $u(\dot{x}^-) < u(x_0^-)$. This means that the bank is offering some contract in the set $A = \{x^- \mid u(x^-) \leq u(\dot{x}^-)\}$ with a positive probability $f_B(x^-)$. Note that by claim 4, these offers are not accepted by borrowers who have a positive signal from the fintech (since they receive strictly better offers from the fintech) and therefore yield zero profit. Consider $f_B'(x^-)$ such that:

$$f_B'(x^-) = \begin{cases} 0 & , \quad x^- \in A \\ f_B(x^-) & , \quad x^- \notin A, \quad x^- \neq x_0^- \\ f_B(x^-) + \int\limits_A f_B(x^-).dx^- & , \quad x^- = x_0^- \end{cases}$$

This constitutes a profitable deviation, since it preserves the same profit from contracts that are not in A, and replaces contracts in A by contract x_0^- which yields positive profit for the bank.

Claim 6. *In a mixed strategy equilibrium in undominated strategies, bank's profit is:*

$$\Pi_B(\hat{E}) = \lambda(1-\sigma)\pi_B^H(x_0^-) = \lambda\pi_B^H(x_1^-)$$

Proof of claim 6:

a) Assume that there exist an equilibrium $\hat{E}'$ such that $\Pi_B(\hat{E}) = k < \lambda(1-\sigma)\pi_B^H(x_0^-)$. If the bank offers a contract $\dot{x}^- \to x_0^-$ such that $u(\dot{x}^-) > u(x_0^-)$, given that the fintech does not play a weakly dominated strategy, all borrowers for whom the fintech have a negative signal accept it. By choosing $\dot{x}^-$ close enough to x_0^-, the bank's profit approaches to $(1-\sigma)\pi_B^H(x_0^-)$ and therefore can be higher than any $k < \lambda(1-\sigma)\pi_B^H(x_0^-)$. Therefore, there exist a profitable deviation.

b) Assume that there exist an equilibrium $\hat{E}'$ such that $\Pi_B(\hat{E}) > \lambda(1-\sigma)\pi_B^H(x_0^-)$. Then there should exist $\dot{x}^-$ offered by the bank such that $\pi_B^H(\dot{x}^-) > \pi_B^H(x_0^-)$ with a positive probability $f_B(\dot{x}^-)$, and

$$\lambda\bigg((1-\sigma)F_F^-(u(\dot{x}^-)) + \sigma F_F^+(u(\dot{x}^-))\bigg)\pi_F^H(\dot{x}^-) > \lambda(1-\sigma)\pi_B^H(u(x_0^-)).$$

This implies that either $F_F^-(u(\dot{x}^-)) = 1$ and $F_F^+(u(\dot{x}^-)) = 0$, or $F_F^+(u(\dot{x}^-)) > 0$. Note that, by claim 4, $F_F^+(u(\dot{x}^-)) > 0$ implies that $F_F^-(u(\dot{x}^-)) = 1$. In that case, if fintech offers a contract $\ddot{x}^-$ such that $u(\ddot{x}^-) \in [u(\dot{x}^-), u(x_0^-)]$, it will be accepted by a positive probability $f_B(\dot{x}^-)$ or higher. Hence, the fintech can deviate and have a positive profit from an offer to borrowers with a negative signal, which is in contradiction to claim 5.

Claim 7. *The following mixed strategies constitute an equilibrium:*

$$M_B = \{x^- \mid u(x_0^-) \le u(x) \le u(x_1^-)\},$$

$$F_B(u(x^-)) = \frac{\bar{w} - u(x_1^-)}{\bar{w} - u(x^-)}, \quad \forall x^- \in M_B$$

$$M_F^+ = \{x^+ \mid u(x_0^-) \le u(x) \le u(x_1^-)\}.$$

$$F_F^+(u(x^+), x^-) = F_F^+(u(x^+)) = \frac{(1-\sigma)(1+\beta)(u(x^+) - u(x_0^-))}{\sigma(\bar{w} - (1+\beta)u(x^+))}, \quad \forall (x^+, x^-) \in M_F$$

$$M_F^- = \{x^- \mid u(\underline{x}^-)) \le u(x) < u(x_0^-)\}, \ \textit{for some } \underline{x}^- \ \textit{s.t } u(\underline{x}^-) < u(x_0^-),$$

$$F_F^-(x^+, u(x^-)) = F_F^-(u(x^-)) \le \frac{\bar{w} - (1+\beta)u(x_0^-)}{\bar{w} - (1+\beta)u(x^-)}, \quad \forall (x^+, x^-) \in M_F.$$

Proof of claim 7: We show that there exist no profitable deviation from these strategies.

a) **No deviation for the bank:** For any contract $x' \in M_B$, the profit of the bank writes:

$$\Pi_B(x', \hat{X}_F) = \lambda\bigg((1-\sigma)\pi_B^h(x') + \sigma F_F^+(u(x'))\pi_B^h(x')\bigg)$$

$$= \lambda\bigg((1-\sigma)(\bar{w} - (1+\beta)u(x')) + \sigma(\bar{w} - (1+\beta)u(x'))\frac{(1-\sigma)(1+\beta)(u(x') - u(x_0^-))}{\sigma(\bar{w} - (1+\beta)u(x'))}\bigg)$$

$$= \lambda\bigg((1-\sigma)(\bar{w} - (1+\beta)u(x_0^-))\bigg) = \lambda(1-\sigma)\pi^h(x_0^-) = \lambda\pi^h(x_1^-).$$

Hence, the bank is indifferent among all contracts in M_B.

For any contract x' on the IC line above x_0^- (such that $u(x') < u(x_0^-)$), bank's profit writes:

$$\Pi_B(x', \hat{X}_F) = \lambda\bigg((1-\sigma)F_F^-(u(x'))\pi_B^h(x') + \sigma F_F^+(u(x'))\pi_B^h(x')\bigg)$$

$$= \lambda(1-\sigma)F_F^-(u(x'))(\bar{w} - (1+\beta)u(x')) \leq \lambda(1-\sigma)\pi^h(x_0^-) = \lambda\pi^h(x_1^-).$$

Hence, the bank does not have a profitable deviation from offering x' on the IC line above x_0^-.

Moreover, if the bank offers a contract on the IC line below x_1^- (such that $u(x') > u(x_1^-)$), all good-type borrowers accept it and bank's profit will be $\Pi(x', \hat{X}_F) = \lambda\pi_B^h(x') < \lambda\pi^h(x_1^-)$, which does not provide a profitable deviation.

b) **No deviation for the fintech:** First consider fintech's offer to borrowers with negative signal. Since $\mathrm{Sup}\{u(x) \mid x \in M_F^-\} \leq \min\{u(x) \mid x \in M_B\}$, offer X_F^- is not accepted by any borrower and yields zero profit, in line with claim 5

Consider fintech's offer to borrowers with a positive signal. For any contract $x' \in M_F^+$, fintech's profit writes:

$$\Pi_F(x', \hat{X}_B) = \lambda\sigma F_B(u(x'))\pi_F^h(x') = \lambda\sigma(\bar{w} - u(x'))\frac{\bar{w} - u(x_1^-)}{\bar{w} - u(x')} = \lambda\sigma(\bar{w} - u(x_1^-)) = \lambda\sigma\pi_F^h(G(x_1^-)).$$

Hence, the fintech is indifferent among all contracts in M_F^+. Also, any contract x' such that $u(x') < u(x_0^-)$ is not accepted by the high-type borrower and yields zero profit. Moreover, for any contract x' such that $u(x') > u(x_1^-)$, fintech's profit writes:

$$\Pi_F^+(x', X_B) = \lambda\sigma\pi_F^h(x') < \lambda\sigma\pi_F^h(G(x_1^-)).$$

Therefore, fintech does not have a profitable deviation for offers to borrowers with a positive signal.

Claim 8. *Any equilibria in undominated mixed strategies has payoffs equivalent to the equilibrium characterized in claim 7.*

Proof of claim 8:

a) First note that, claims 5 and 6 uniquely specify the support of a mixed strategy equilibrium. In particular, the support of bank's offers must be $M_B = \{x^- \mid u(x_0^-) \leq u(x) \leq u(x_1^-)\}$. If bank offers x^- such that $u(x^-) < u(x_0^-)$, the fintech can have positive profit from his offers to borrowers with a bad signal (as described in the proof of claim 6) which violates claim 5. Also, offering x^- such that $u(x^-) > u(x_1^-)$ violates claim 6. Given M_B, we must have $M_F^+ = \{x^+ \mid u(x_0^-) \leq u(x) \leq u(x_1^-)\}$, so that the indifference condition for a mixed strategy equilibrium can hold true for both lenders.

b) Given the supports M_B and M_F^+, the distributions $F_F^+(u(x^+))$ and $F_B(u(x^-))$ are the unique strategies for which the indifference criteria of a mixed strategy equilibrium are satisfied.

c) $F_F^-(u(x^-))$ as characterized in claim 7 is not unique. However, since these offers are not accepted by any borrower and only serve as a threat to prevent profitable deviations for the bank, they do not affect the payoffs.

$\square$

Proof. of Proposition 2:

We first solve for the payoffs and welfare in equilibrium, and then analyze their behavior with respect to σ.

a) **Profits.** Given that lenders are indifferent among all contracts in their supports, we can write their profit in equilibrium as:

$$\Pi_B(\hat{E}) = \int_{x_0^-}^{x_1^-} \pi_B(x, \hat{X}^F).dx = \lambda(1-\sigma)\pi_B^H(x_0^-) = \lambda(1-\sigma)[\bar{w} - (1+\beta)u(x_0^-)]$$

$$\Pi_F(\hat{E}) = \int_{G(x_0^-)}^{G(x_1^-)} \pi_B(\hat{X}^B, x).dx = \lambda\sigma\pi_F^H(G(x_1^-)) = \lambda\sigma[\bar{w} - u(x_1^-)]$$

Note that since

$$\pi_B^H(x_1^-) = \bar{w} - (1+\beta)u(x_1^-) = (1-\sigma)\pi_B^H(x_0^-) = (1-\sigma)(\bar{w} - (1+\beta)u(x_0^-)),$$

we can write

$$u(x_1^-) = u(x_0^-) + \sigma(\frac{\bar{w}}{1+\beta} - u(x_0^-)).$$

Denoting $u_0 \equiv u(x_0^-)$ and $u_1 \equiv u(x_1^-)$, we have:

$$\Pi_B(\sigma) = \lambda(1-\sigma)[\bar{w} - (1+\beta)u_0]$$

$$\Pi_F(\sigma) = \lambda\sigma\left[\bar{w} - u_0 - \sigma\left(\frac{\bar{w}}{1+\beta} - u_0\right)\right]$$

b) **Welfare.** We denote the social welfare of an equilibrium by $W(\hat{E})$. In equilibrium, all high-type borrowers accept a loan offer, while low-type borrowers do not accept any offer. A contract x^+ with no collateral generates welfare $\bar{w}$ and results in no inefficiency. A contract x^- on the IC^0 line offered by the bank generates welfare $\bar{w} - \beta u(x^-)$, and hence has an inefficiency equal to $\beta u(x^-)$. We can then write the social inefficiency of an equilibrium as:

$$SI(\hat{E}) \equiv \lambda \bar{w} - W(\hat{E}) = \int_{x_0^-}^{x_1^-} \lambda f^B(x^-)[1 - \sigma + \sigma F_F^+(x^-)]\beta u(x^-).dx^-,$$

which is the inefficiency of the contracts on the IC^0 line offered by the bank and accepted by high-type borrowers.

From the proof of proposition 1, for $x \in M^B = \{x^- \mid u_0 \leq u(x^-) \leq u_1\}$[50]:

$$f^B(u(x_0^-)) = \frac{\bar{w} - u(x_1^-)}{\bar{w} - u(x_0^-)}, \text{ and } f^B(u(x)) = \frac{\bar{w} - u(x_1^-)}{(\bar{w} - u(x))^2}, \ \ x \neq x_0^-,$$

$$F_F^+(u(x)) = \frac{(1-\sigma)(1+\beta)(u(x) - u(x_0^-))}{\sigma(\bar{w} - (1+\beta)u(x))}.$$

Since we are specifying any contract $x \in M^B$ by $u(x)$, we further simplify the notation by using $u = u(x)$. We can then write:

$$SI(\hat{E}) = \lambda(1-\sigma)\frac{\bar{w} - u_1}{\bar{w} - u_0}\beta u_0 + \int_{u_0}^{u_1} \lambda \frac{\bar{w} - u_1}{(\bar{w} - u)^2}\left(1 - \sigma + \sigma[\frac{(1-\sigma)(1+\beta)(u - u_0)}{\sigma(\bar{w} - (1+\beta)u)}]\right)\beta u.du$$

$$= \lambda(1-\sigma)\beta u_0 \frac{\bar{w} - u_1}{\bar{w} - u_0} + \lambda\beta(1-\sigma)(\bar{w} - u_1)(\bar{w} - (1+\beta)u_0)\int_{u_0}^{u_1} \frac{u}{(\bar{w} - u)^2(\bar{w} - (1+\beta)u)}.du$$

Calculating the integral and simplifying yields

$$SI(\hat{E}) = \lambda(1-\sigma)\beta u_0 \frac{\bar{w} - u_1}{\bar{w} - u_0}$$

$$+\lambda(1-\sigma)(\bar{w} - u_1)(\bar{w} - (1+\beta)u_0)\frac{1}{\beta\bar{w}}\left[\ln\left(\frac{\bar{w} - u_1}{(1-\sigma)(\bar{w} - u_0)}\right) + \frac{1}{\bar{w} - u_0} - \frac{1}{\bar{w} - u_1}\right]$$

$$= \lambda(1-\sigma)((1+\beta)u_0 - u_1) + \frac{\lambda}{\beta\bar{w}}(1-\sigma)(\bar{w} - u_1)(\bar{w} - (1+\beta)u_0)\ln\left(\frac{\bar{w} - u_1}{(1-\sigma)(\bar{w} - u_0)}\right)$$

We denote $\alpha \equiv \frac{\bar{w}}{1+\beta} - u_0 > 0$, so that $u_1 = u_0 + \alpha\sigma$. Also, we denote $A \equiv \bar{w} - u_0$, therefore $\bar{w} - (1+\beta)u_0 = \alpha(1+\beta)$, and $\bar{w} - u_1 = A - \alpha\sigma$. We can then write:

$$W(\sigma) = \lambda\bar{w} - SI(\sigma) = \lambda\left[\bar{w} - (1-\sigma)\left(\beta u_0 - \alpha\sigma + \frac{\alpha(1+\beta)}{\beta\bar{w}}(A - \alpha\sigma)\ln(\frac{A - \alpha\sigma}{A(1-\sigma)})\right)\right]$$

[50]Note that $F_B(u(x))$ has a mass point at x_0^-

c) Given the expressions for $\Pi_B(\sigma)$, $\Pi_F(\sigma)$, and $W(\sigma)$, the utility of borrowers in equilibrium writes:

$$U(\sigma) = W(\sigma) - \Pi_B(\sigma) - \Pi_F(\sigma)$$

$$U(\sigma) = \lambda\left[\bar{w} - (1-\sigma)\left(\beta u_0 - \alpha\sigma + \frac{\alpha(1+\beta)}{\beta\bar{w}}(A-\alpha\sigma)\ln(\frac{A-\alpha\sigma}{A(1-\sigma)})\right)\right]$$
$$-\lambda(1-\sigma)[\bar{w} - (1+\beta)u_0] - \lambda\sigma(\bar{w} - u_0 - \alpha\sigma),$$

which can be simplified to

$$U(\sigma) = \lambda\left[u_0 + \alpha\sigma - \frac{\alpha(1+\beta)}{\beta\bar{w}}(A-\alpha\sigma)(1-\sigma)\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right)\right]$$

1. Note that $\frac{A-\alpha\sigma}{A(1-\sigma)}$ is continuous and increasing in σ, going from 1 at $\sigma = 0$ to $+\infty$ at $\sigma = 1$. Hence $U(\sigma)$ is continuous. Taking the derivative w.r.t σ yields:

$$\frac{1}{\lambda}\frac{\partial U(\sigma)}{\partial\sigma} = \alpha - \frac{\alpha(1+\beta)}{\beta\bar{w}}\left[(2\alpha\sigma - \alpha - A)\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right) + A - \alpha)\right].$$

Note that $\frac{\alpha(1+\beta)}{\beta\bar{w}}(A-\alpha) = \alpha$, and therefore:

$$\frac{\partial U(\sigma)}{\partial\sigma} = (2\alpha\sigma - \alpha - A)\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right).$$

Note that $A + \alpha - 2\alpha\sigma = (A-\alpha\sigma) - \alpha(\sigma - 1) = (\bar{w} - u_1) + \alpha(1-\sigma) > 0$, and $\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right) \geq 0$. Therefore:

$$\frac{\partial U(\sigma)}{\partial\sigma} \geq 0 \;\; \forall\sigma \in [0,1],$$

and hence $u(\sigma)$ is strictly increasing.

2. Bank's profit, $\Pi_B(\sigma) = \lambda\alpha(1+\beta)(1-\sigma)$, is continuous and linearly decreasing in σ.

Fintech's profit is $\Pi_F(\sigma) = \lambda\sigma(A - \alpha\sigma)$, which is quadratic in σ and has a local maximum in $(0,1)$ if:

$$\frac{A}{2\alpha} = \frac{\bar{w} - u_0}{2(\frac{\bar{w}}{1+\beta} - u_0)} < 1.$$

Note that as $\gamma \to 0$, we have $\pi_B^H(x_0^-) = \bar{w} - (1+\beta)u_0 \to 0$, therefore::

$$\lim_{\gamma\to 0}\frac{\bar{w} - u_0}{2(\frac{\bar{w}}{1+\beta} - u_0)} = +\infty$$

As γ approaches to 1, we have $\beta \to 0$, and therefore:

$$\lim_{\gamma\to 1}\frac{\bar{w} - u_0}{2(\frac{\bar{w}}{1+\beta} - u_0)} = \frac{1}{2}$$

Hence, there exists a threshold γ_F such that for $\gamma < \gamma_F$ fintech's profit is strictly increasing, and for $\gamma > \gamma_F$, fintech's profit has a local maximum in $(\frac{1}{2}, 1)$.

3. First note that $W(1) = \bar{w} > W(0) = \bar{w} - \beta u_0$. The first derivative w.r.t σ writes:

$$W'(\sigma) = \frac{\partial W(\sigma)}{\partial \sigma} = \lambda \Bigg[\underbrace{(\beta u_0 - 2\alpha\sigma)}_{\frac{1}{\lambda}(\Pi'_B(\sigma)+\Pi'_F(\sigma))} + \underbrace{\frac{\alpha(1+\beta)}{\beta\bar{w}}(A+\alpha-2\alpha\sigma)\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right)}_{\frac{1}{\lambda}U'(\sigma)} \Bigg].$$

We have $W'(0) = \beta u_0 > 0$, and $\lim_{\gamma\to 1} W'(\sigma) = +\infty$. As shown above, we have $U'(\sigma) > 0$ for all σ. However, $\Pi'_B(\sigma) + \Pi'_F(\sigma) = \beta u_0 - 2\alpha\sigma$ can become negative at some $\sigma > 0$, if α is sufficiently large. Note that:

$$\lim_{\gamma\to 0} \beta = \frac{\bar{w}}{u_0} - 1 > 0 \ , \ \lim_{\gamma\to 1} \beta = 0^+ \ , \ \lim_{\gamma\to 0} \alpha = 0^+ \ , \ \lim_{\gamma\to 1} \alpha = A^-.$$

Hence, for sufficiently small γ, $U(\sigma)$ and $\Pi'_B(\sigma) + \Pi'_F(\sigma)$ are both positive and $W(\sigma)$ is everywhere increasing.

We show that, for sufficiently large γ, we can have $\Pi'_B(\sigma) + \Pi'_F(\sigma)$ sufficiently negative such that $W(\sigma)$ becomes decreasing in some range of σ.

The second derivative of $W(\sigma)$ writes:

$$W''(\sigma) = \frac{\partial^2 W(\sigma)}{\partial \sigma^2} = -2\lambda\alpha \Bigg[1 + \underbrace{\frac{\alpha(1+\beta)}{\beta\bar{w}}\ln\left(\frac{A-\alpha\sigma}{A(1-\sigma)}\right)}_{Q_1(\sigma)} + \underbrace{\frac{\alpha(1+\beta)(A-\alpha)(2\alpha\sigma-\alpha-A)}{2\beta\bar{w}(A-\alpha\sigma)(1-\sigma)}}_{Q_2(\sigma)}\Bigg]$$

Note that $Q_1(\sigma)$ is positive and strictly increasing, while $Q_2(\sigma)$ is negative and strictly decreasing [51]. This suggests that the second derivative, $W''(\sigma)$, can have either one or no root. At $\sigma = 0$, we have

$$W''(0) = -\lambda\left(2\alpha - \frac{\alpha(1+\beta)(A-\alpha)(A+\alpha)}{2\beta\bar{w}A}\right) = -\lambda(2\alpha - \frac{\alpha(A-\alpha)}{A}) = \frac{-\lambda\alpha\beta\bar{w}}{A(1+\beta)} < 0,$$

where the simplification is done by replacing by $A - \alpha = \frac{\beta\bar{w}}{1+\beta}$. Also note that:

$$\lim_{\sigma\to 1} W'(\sigma) = +\infty \ \rightarrow \ \lim_{\sigma\to 1} W''(\sigma) = +\infty.$$

Therefore, $W''(\sigma)$ has a unique root, which we denote by σ^*. Welfare function $W(\sigma)$ is concave for $\sigma < \sigma^*$, and convex for $\sigma > \sigma^*$. This implies that, if the first derivative is positive at this point, $W''(\sigma^*) > 0$, welfare function must be strictly increasing. Conversely, if $W''(\sigma^*) < 0$, welfare function must have a local maximum at some $\sigma < \sigma^*$ and a local minimum at some $\sigma > \sigma^*$.

[51] $Q'_2(\sigma) = \frac{-2\alpha\sigma^2 - 2\alpha(\alpha+A)\sigma - (A^2+\alpha^2)}{(A-\alpha\sigma)^2(1-\sigma)^2} < 0, \forall \sigma \in (0,1)$

The first derivative at the root of the second derivative writes:

$$W'(\sigma^*) = \frac{(2\alpha\sigma - \alpha - A)^2}{2(1-\sigma)(A-\alpha\sigma)} - \alpha(2+\beta).$$

Note that:

$$\lim_{\gamma\to 1,\ \alpha\to A^-,\ \beta\to 0^+} \alpha(2+\beta) = 2\alpha^+ > 2\alpha.$$

Also note that

$$\lim_{\alpha\to A^-} (2\alpha\sigma - \alpha - A)^2 < 4\alpha^2(1-\sigma)^2, \text{ and } \lim_{\alpha\to A^-} 2(1-\sigma)(A-\alpha\sigma) > 2\alpha(1-\sigma)^2.$$

Hence,

$$\lim_{\gamma\to 1,\ \alpha\to A^-,\ \beta\to 0^+} \frac{(2\alpha\sigma - \alpha - A)^2}{2(1-\sigma)(A-\alpha\sigma)} = 2\alpha^- < 2\alpha.$$

Therefore,

$$\lim_{\gamma\to 1,\ \alpha\to A^-,\ \beta\to 0^+} W'(\sigma^*) < 0.$$

Hence, for γ sufficiently high (β sufficiently close to zero and α sufficiently close to A), $W(\sigma^*)$ is negative, implying that, in this case, welfare function becomes decreasing for some $\sigma \in (0,1)$. This proves that, for sufficiently large γ, the welfare function $W(\sigma)$, is non-monotone and exhibits a local maximum and minimum.

Finally, note that $\Pi'_B(\sigma) + \Pi'_F(\sigma) = \beta u_0 - 2\alpha\sigma$ becomes strictly more decreasing in σ as γ increases (α increases):

$$\frac{\partial(\Pi'_B(\sigma) + \Pi'_F(\sigma))}{\partial\gamma} < 0, \ \ \forall\sigma \in [0,1]$$

Moreover, $U(\sigma)$ is a strictly increasing function in the range $[\bar{w} - \beta u_0, \bar{w}]$, and becomes strictly less increasing in σ as γ increases (β decreases):

$$\frac{\partial U'(\sigma)}{\partial\gamma} < 0, \ \ \forall\sigma \in [0,1]$$

Hence, $\frac{\partial W(\sigma^*)}{\partial\gamma} < 0$, for all $\sigma \in [0,1]$. This implies that, if $W(\sigma)$ is non-monotone for some γ', it must be non-monotone for all $\gamma > \gamma'$. Recall that $W(\sigma)$ is strictly increasing for $\gamma \to 0$, and non-monotone for $\gamma \to 1$. Thus, there exists a unique γ_W such that, $W(\sigma)$ is strictly increasing for $\gamma < \gamma'$, and is non-monotone, exhibiting a local maximum and minimum, for $\gamma > \gamma'$.

$\square$

Proof. of Proposition 3:

1. It follows directly from proposition 2.

2. It follows directly from proposition 2.

3. From proposition 2, fintech's profit $\Pi_F(\sigma)$ is strictly increasing in σ for $\gamma < \gamma_F$. In such cases, $\hat{\sigma}^F = \bar{\sigma}$, and the fintech prefers open banking with full data sharing.

   Assume that $\gamma > \gamma_F$, such that fintech's profit is inverse U-shaped and reaches its maximum at $\sigma^F_{max} \in (0, 1)$. Three cases are possible:

   a) If $\sigma^F_{max} \leq \bar{\sigma}$, then $\hat{\sigma}^F = \bar{\sigma}$, and the fintech prefers open banking with full data sharing.

   b) If $\sigma^F_{max} \geq \underline{\sigma}$, then $\hat{\sigma}^F = \underline{\sigma}$, and the fintech prefers closed banking.

   c) If $\sigma^F_{max} \in (\underline{\sigma}, \bar{\sigma})$, then fintech prefers partial data sharing such that $\sigma = \sigma^F_{max}$.

4. From proposition 2, welfare $W(\sigma)$ is strictly increasing in σ for $\gamma < \gamma_W$. In such cases, $\hat{\sigma}_W = \bar{\sigma}$, and the fintech prefers open banking with full data sharing.

   Assume that $\gamma > \gamma_W$, such that welfare is bimodal and has a local maximum at σ^{max}_W, and a local minimum at σ^{min}_W, and is decreasing in the interval $(\sigma^{max}_W, \sigma^{min}_W)$. Three cases are possible:

   a) If $\bar{\sigma} \leq \sigma^{max}_W$ or $\underline{\sigma} \geq \sigma^{min}_W$, then $\hat{\sigma}_W = \bar{\sigma}$ and open banking with full data sharing maximizes the total welfare.

   b) If $\sigma^{max}_W \in (\underline{\sigma}, \bar{\sigma})$, then open banking with full data sharing maximizes the welfare only if $W(\bar{\sigma}) \geq W(\sigma^{max}_W)$. Otherwise, partial data sharing such that $\sigma = \sigma^{max}_W$ is socially optimal.

   c) If $\sigma^{max}_W < \underline{\sigma}$, then open banking with full data sharing maximizes the welfare only if $W(\bar{\sigma}) \geq W(\underline{\sigma})$. Otherwise, closed banking is socially optimal.

□

Proof. of Lemma 1:
Recall from the proof of Proposition 2 that:

$$\Pi_B(\sigma) = \lambda\alpha(1 + \beta)(1 - \sigma),$$

$$\Pi_F(\sigma) = \lambda\sigma(A - \alpha\sigma).$$

Therefore,

$$\Pi'_B(\sigma) + \Pi'_F(\sigma) = -\alpha(1 + \beta) + A - 2\alpha\sigma = \beta u_0 - 2\alpha\sigma,$$

where the simplification is done by replacing $A-\alpha=\frac{\beta\bar{w}}{1+\beta}$. It is straightforward that, there exist a threshold γ_{BF} (a threshold in α) at which: $\Pi'_B(1)+\Pi'_F(1)=0$.

Hence, for $\gamma \leq \gamma_{BF}$ the joint profit is strictly increasing, and for $\gamma > \gamma_{BF}$ the joint profit is inverse U-shaped and has a local maximum at some $\sigma \in (0,1)$.

Recall that $\Pi_B(\sigma)$ is always strictly decreasing, while $\Pi_F(\sigma)$ is strictly increasing for $\gamma \leq \gamma_F$ and inverse U-shaped for $\gamma > \gamma_F$. This implies that, for $\gamma = \gamma_{BF}$, we have $\Pi'_F(\sigma) > 0$ for all σ. Therefore we must have $\gamma_{BF} < \gamma_F$.

Similarly, since $U(\sigma)$ is strictly increasing for $\gamma < \gamma_W$, for $\gamma = \gamma_{BF}$, we have $W'(\sigma) > 0$ for all σ. Therefore we must have $\gamma_{BF} < \gamma_W$.

□

Proof. of Proposition 4:

1. If $\gamma < \gamma_{BF} < \gamma_W$, welfare and joint profit are both strictly increasing. Hence, $\hat{\sigma}_{BF} = \hat{\sigma}_W = \bar{\sigma}$, and the same outcome is obtained under any allocation of property rights.

2. If $\gamma \in (\gamma_{BF}, \gamma_W)$, welfare is strictly increasing in σ, while the joint profit has a local maximum at some $\sigma_{BF}^{max} \in (0,1)$. If $\sigma_{BF}^{max} \in (\underline{\sigma}, \bar{\sigma})$, then $\hat{\sigma}_{BF} = \sigma_{BF}^{max} < \hat{\sigma}_W = \bar{\sigma}$, and assigning property rights to one of the lenders result in lower welfare than open banking with full data sharing.

3. If $\gamma > \gamma_W > \gamma_{BF}$, welfare is bimodal and the joint profit is inverse U-shaped in σ. If $\hat{\sigma}_{BF} = \hat{\sigma}_W = \bar{\sigma}$, the allocation of property rights is irrelevant. Otherwise, open banking is socially optimal if $W(\hat{\sigma}_W) > W(\hat{\sigma}_{BF})$, and allocating property rights to one of the lenders is socially optimal if $W(\hat{\sigma}_W) < W(\hat{\sigma}_{BF})$.

□

Proof. of Proposition 5:

1. If $\gamma < \min\{\gamma_F, \gamma_W\}$, both fintech's profit and welfare are strictly increasing in σ, and hence $\hat{\sigma}_F = \hat{\sigma}_W = \bar{\sigma}$. In this case, fintech chooses the welfare maximizing level of signal informativeness.

2. Assume $\gamma \in [\gamma_F, \gamma_W]$. In that case, fintech's profit is inverse U-shaped and welfare is strictly increasing in σ. If $\hat{\sigma}_F < \bar{\sigma} = \hat{\sigma}_W$, the fintech under-invests in data analytics.

3. Assume $\gamma \in [\gamma_W, \gamma_F]$. In this case, welfare is bimodal and fintech's profit is strictly increasing in σ. If $\hat{\sigma}_W < \bar{\sigma} = \hat{\sigma}_F$, the fintech over-invests in data analytics.

4. If $\gamma > \max\{\gamma_F, \gamma_W\}$, fintech's profit is inverse U-shaped and welfare is bimodal in σ. If $\hat{\sigma}_W = \hat{\sigma}_F$, fintech's incentives aligns with those of society. Otherwise, the fintech either under-invests (when $\hat{\sigma}_W > \hat{\sigma}_F$) or over-invests (when $\hat{\sigma}_W < \hat{\sigma}_F$).

$\square$