The Fintech-Bank Lending Ecosystem*

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Abstract

We develop a model of a lending market featuring banks with low funding costs and fintech lenders with superior borrower screening technology. We derive and characterize the fintech-bank lending ecosystem, where the two types of lenders compete to lend and optimally collaborate by trading data. After providing loans to risky borrowers underserved by banks, fintech lenders serve as an on-ramp to the financial system by selling borrowers' credit history data to banks, who take over subsequent lending. We show how different regulatory regimes and market environments affect the optimal form of fintech-bank collaborations. Facilitating fintech-bank collaborations and data tradings can reduce borrowing costs, improve financial inclusion, and reduce excessive investment in financial technology.

JEL Classifications: G21, G23, G33, O32, O34, L84

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1 Introduction

Compared to traditional banks, one advantage of fintech and bigtech lenders is the ability to screen borrowers through multiple means, such as using alternative data sources and deploying specialized statistical models.[1] One example is the Ant Financial Group, which uses the Taobao e-commerce data to produce its own credit scores for borrowers, increasing financial inclusion among borrowers with little or no credit history (Hau et al. 2018). Traditional banks may be unable to emulate the financial analytics capability due to more stringent regulation, legacy information technology, or organization frictions (Stulz 2019). Nevertheless, banks have lower funding costs due to fintech lenders' inability to take insured deposits and access central-bank liquidity. However, how the development of fintech lenders affect the traditional banking system is not obvious (Vives, 2017). Fintech lenders and traditional banks each have distinct comparative advantages. While they may compete in some dimensions for some segments of borrowers, they can also gain from cooperating. For example, traditional banks and fintech lenders can jointly lend to specific borrowers, or —with recent advances in data tokenization and smart contracting—traditional banks may profit from purchasing borrowers' credit history data from fintech lenders. How do fintech lenders and banks collaborate in the lending market? How do different types of fintech-bank collaboration models affect the cost of borrowing, fintech investments, and social welfare?

To answer these questions, we develop a model of a lending market featuring banks with low funding costs and fintech lenders with superior borrower screening technology. In the model, fintech lenders add value to the economy by making credit cheaper and accessible to risky borrowers otherwise under-served by traditional banks. By lending to these risky borrowers, fintech lenders accumulate borrowers' credit history data, which is valuable for banks' lending decisions and thus gives rise to potential fintech-bank collaborations. We show that the optimal collaboration features data selling, in which fintech lenders serve as an on-ramp to the financial system by selling bor-

[1] For example, Berg et al. (2020) show that digital footprints improve credit scoring, Gao et al. (2018) show that the text in borrowing applications can predict defaults, and Fuster et al. (2021) show that machine learning models can improve default ratios from the banks' perspective, although they also document that Blacks and Hispanics were less likely to benefit from such innovations.

rowers' credit history data to banks who take over subsequent lending. However, executing such a data-selling contract can be costly because it requires that the credit history data be ex-ante contractable and exclusively sold to one bank. Allowing data selling can reduce borrowing rates and improve financial inclusion, while its effect on social welfare is ambiguous. Our model suggests that fintech-bank collaborations are more likely to improve social welfare in countries where the funding-cost difference between fintech lenders and banks is slight.

Now, let us describe the model in detail. There is a continuum of borrowers who need to finance their projects with private types. Specifically, each borrower has an investment project that can be either a good or a bad type. A good-type project yields positive NPV, while a bad-type project has negative NPV because it may fail and generate zero recovery value randomly. Borrowers can apply for financing from two types of lenders: banks and fintech lenders. We assume that banks have lower funding costs while fintech lenders possess superior screening technologies that can help detect bad-type projects. Note that a fintech lender's superior screening technology can reduce lending risks and make credits more accessible to risky borrowers. We show that under certain conditions, fintech lenders can improve financial inclusion by lending to risky borrowers otherwise under-served by the traditional banking system.

By lending to a risky borrower underserved by banks, the fintech lender privately owns the credit history data of the borrower. In the model, conditional on no defaults, the borrower's perceived credit quality improves over time. As such, the borrower's credit history data become more valuable over time because the lender can capture the information-monopoly rent in servicing the borrower's future financing needs. Consequently, traditional banks—who have lower funding costs than fintech lenders but may not have found it worthwhile to lend to high-risk borrowers—may find it profitable to collaborate with fintech lenders so that they can utilize their funding-cost advantages in lending to borrowers with good credit histories.

We explore how different types of contractual environments lead to different types of collaboration models between fintech lenders and banks. When payments cannot be contingent on the content of the credit history data, the optimal fintech-bank collaboration is a *joint-lending* contract in which a fintech lender and a bank agree on the share of a loan that each will contribute and the price the bank is willing to pay to the fintech lender for originating the loan. In joint lending, the fintech lender has skin in the game by holding a fraction of the loan.[2] When we extend the model to allow for positive recovery values in default, the optimal joint lending contract takes the form of a securitized loan, whereby banks hold senior tranches and fintech lenders hold junior tranches of the loan. These contracts resemble asset-back securities, which we have also seen in practice. For example, Ant Financial sold almost $600 million in small-loan-backed securities in 2016.[3]

When payments can be contingent on the content of the credit history data, the optimal fintech-bank collaboration features a *data-selling* contract in which the fintech lender sells the borrower's credit history data to a bank. Unlike the joint lending contract, which can only specify the share to lend jointly, the data-selling contract is richer. Not only does it specify the fintech lender's share of the loan, but it also specifies when the fintech lender can sell the data to the bank. Under such a contract, the fintech lender can have skin in the game to exert screening effort by holding a fraction of the loan after data selling and by financing the loan before data selling. In the optimal contract, the fintech lender bears all the lending risks for the initial period and then sells the credit history data to the bank, which will fully finance the loan going forward. In practice, this collaboration model involves a bank first querying the fintech lender upon a new loan application to check whether the borrower has had a prior relationship with the fintech lender. Note that due to the non-rivalrous nature of data, executing the data-selling contract also requires a mechanism that allows for exclusive data selling to one bank.

Instead of selling the borrower's credit history data, the fintech lender can directly sell the loan to the bank. We call this type of collaboration a *loan-selling* contract. The difference between a data selling and a loan selling contract is subtle. Under a data selling contract, the bank pays the fintech lender for collaboration per unit of borrower with a non-empty credit history. However, under a loan selling contract, the fintech lender only pays the fintech lender per unit of borrower

[2] In practice, joint lending by fintech lenders like Ant Financial Group and partner banks are roughly 2% and 98%, respectively. See https://news.boomberglaw.com/banking-law/ant-faces-another-setback-in-curbs-on-joint-lending-with-banks

[3] See https://www.reuters.com/article/alibaba-debt-bonds-idUKL4N1DT17J/

with good credit history. Compared to the data selling contract, the loan selling contract gives the fintech lender an additional disincentive for screening as the payment for collaboration decreases in the fintech lender's screening effort.

Among these different contracts, the data selling contract, whenever possible, is optimal because data selling is a more effective contract to incentivize fintech screening. Compared to the joint lending contract, the data selling contract has the fintech lender bear the potential loan losses for the initial period when the loan has the highest default risks, thereby giving the fintech lender a higher screening incentive, all else being equal. Compared to the loan selling contract, the data selling contract reduces the moral hazard associated with screening-sensitive service fee payment in fintech-bank collaborations.

In sum, allowing fintech-bank collaborations can reduce borrowing costs and improve financial inclusion. The optimal form of collaboration features data selling, in which fintech lenders provide loans to borrowers underserved by banks and later serve as an on-ramp to the financial system by selling borrowers' credit history data to banks who take over subsequent lending. Introducing fintech-bank collaborations tends to reduce the fintech lender's investment in screening technology because, in a fintech-bank collaboration, fintech screening has the opportunity cost of giving up cheaper bank funding.

Motivated from the viewpoint of a financial regulator, we consider a social planner that can choose the level of screening technology but is also subject to information frictions on borrower type and cannot directly finance the fintech lender (at low costs). As a baseline, without collaboration, the fintech lender overinvests in screening technology compared to the socially optimal level. The overinvestment in screening technology can be interpreted as harvesting too much personal data that generates large disutility about privacy violations, building overly sophisticated machine learning models, or overhiring data scientists relative to the socially optimal level. Therefore, allowing fintech-bank collaborations, which tend to reduce fintech investment in screening technology, can mitigate the over-investment problem and improve social welfare. In other words, encouraging fintech-bank collaborations and data selling can be viewed as an easy-to-implement policy to reduce over-investment in fintech technology and to lower concerns about data privacy.

Nevertheless, allowing fintech-bank collaborations and credit history data trading may lead to underinvestment in screening technologies. Therefore, we do not expect to see a one-size-fits-all financial regulation on the lending ecosystem but expect to find different types of economies reacting differently. For instance, our model suggests that countries where banks have significant funding-cost advantages over fintech lenders may want to limit fintech-bank collaborations and restrict data trading. In contrast, countries with little funding-cost difference between fintech lenders and banks can benefit from encouraging fintech-bank collaborations and data trading.

After discussing the related literature, the remainder of the paper is as follows: Section 2 presents the model of a lending ecosystem featuring fintech lenders and traditional banks, Section 3 introduces the market for data sharing, Section 4 discusses policy implications, and Section 5 concludes.

Related Literature

Our research contributes to the nascent literature on financial technology and banking. Parlour et al. (2022) studies the impact of fintech competition in payment services when banks and fintech companies can use payment data to learn about consumers' credit quality. They find that fintech competition in payment services can promote financial inclusion, but it has an ambiguous effect on the loan market. Schweitzer and Barkley (2017) compares traditional bank borrowers and online fintech borrowers and show that the latter resemble applicants who were denied credit by traditional banks (Cole and Sokolyk, 2016), and that bank borrowers showed more satisfaction than online borrowers. The extant research has also studied the relationship between bank size, IT investments, hard information processing, and the collect of soft information (e.g., Carter and McNulty 2005; Berger and Black 2011; DeYoung et al. 2011; Sedunov 2017; He et al. 2021). However, big tech lenders may retain the comparative advantage due to access to alternative data, as in the case with Ant Financial (Hau et al., 2018). Jagtiani and Lemieux (2018) shows that fintech lending penetrates areas underserved by traditional banks.

Our research builds on existing works like Pagano and Jappeli (1993) who study the determinants of and implications when banks choose to share information of borrowers, through the lens of the establishment of a credit bureau. They find that the incentives to share data among banks increase with more technological availability for screening or information, the size of the credit market, and decreases with regulatory safeguards for privacy. They find that increased competition among banks decreases the incentives to share the data, similar to the results in our model. However, they do not consider a setting where membership in a credit bureau is observable and where banks have incentives for dishonest reporting (Semenova 2008). In contrast, we study data agreements in an ecosystem with different types of lenders. Bennardo et al. (2015) shows information sharing between banks can mitigate overborrowing incentives and emphasize that private and social incentives for information sharing are not aligned.

On the value of data, Farboodi et al. (2019) and Jones and Tonetti (2020) show that the value of data has increasing returns in helping borrowers do price differentiation. The latter discusses situations in which data sharing would increase economic efficiency and concludes that giving data rights to consumers who trade-off between privacy and economic gains from selling their data generates an allocation close to socially optimal. He et al. (2023) consider a setting with an open bank whereby borrowers own their borrowing data and find that open banking can leave borrowers worse off even if they could share their own data. Our model consider data selling between different lenders In contrast, in our setting, giving the borrowers their credit history data is not credible because it would reduce fintech lenders' incentives to create screening and creidt histroy data in the first place, causing increased borrowing costs and credit rationing. Our consideration of the market value of credit history also relates to Chatterjee et al. (2020) who develop a structural model to estimate the value of credit scores, although the latter does not consider interactions across financial institutions.

In addition, our research relates to the industrial organization of the financial system, including the consideration of banking competition and fintech on incumbents. Mitchell and Pearce (2011) finds that more competitive lending markets provide minority small business owners with more access. Berger et al. (2015) find that more small bank presence yields more lending with slightly lower failure rates of small borrowers during normal times, but the differences in failure rates disappear during the financial crisis. Fuster et al. (2019) studies how technology affects mortgage origination in terms of processing time and find that fintech lenders process applications faster and adjust supply more elastically than other lenders in response to exogenous mortgage demand. Morse (2015) summaries the peer-to-peer lending market and find that on the investor side, such platforms disintermediates a class of consumer loans and investors can capture the rents. Our research is also relevant for the more recent European regulations aimed at providing a framework for fintech-bank data sharing (Borgogno and Colangelo, 2020).

2 A Model of Fintech Lending

2.1 Setup

Time is continuous and runs to infinity. The economy is populated with three types of agents, borrowers, fintech lenders, and banks. All agents are risk-neutral. Fintech lenders and banks discount cashflows at the rate of ρ, and borrowers discount cashflows at the rate of $\rho_b > \rho$.

Borrowers

There is a continuum of borrowers,[4] which we normalize to be of measure one. At date t_0, each borrower is endowed with an investment project. The project requires 1 dollar of initial investment and generates ydt cashflows per dt unit of time. Whether invested or not, the project matures with poisson rate λ, and if invested, the project generates a terminal cashflow of $X = 1$ at maturity. After the project matures, the borrower exits the economy. The project can be either a good or a bad type. A good-type project never fails, whereas a bad-type project fails with poisson rate γ. For simplicity, we assume that the residual value of a failed project is $L = 0$. Importantly, we assume the type of a project is its borrower's private information. Among all borrowers, π of them have good projects and $1-\pi$ of them have bad projects. π, which is assumed to be public information,

[4]We use the term "borrower" rather than "entrepreneur" or "firm", because the model also applies to both firms as well as individual borrowers who may be seeking consumer loans or trying to reconcile existing debt, to the extent that some borrowers have positive NPV "projects" and others do not.

measures the observable quality of borrowers. We make the following assumption so that the NPV of a good project is positive and that the NPV of a bad project is negative:

Assumption 1. $y \in (\rho, \rho + \eta)$.

Lenders

We assume that the borrower has no net worth, so it has to get external funding to finance its investment project. In order to finance its investment, a borrower has to get external financing from either a traditional bank or a fintech lender.[5] These two types of financiers are long lived, deep pocketed, and face perfect competition among each other. To keep the problem tractable, we restrict our attention to one-period debt.

There are two main differences between traditional banks and fintech lenders in the model. First, we assume traditional banks have lower funding costs due to their deposit-taking ability compared to fintech lenders whose financing typically comes from private markets. Specifically, we assume a bank enjoys bdt units of subsidy per unit of lending during a dt period. The funding-cost difference captures banks' advantage in their access to insured deposits and central bank liquidity. Second, we assume fintech lenders have superior screening technology compared to banks. Each fintech lender has a screening technology that can generate informative signals about the borrower's creditworthiness (e.g., Council 2021). Specifically, a fintech lender can exert costly effort and receive a binary signal $s \in \{g, b\}$ (for good and bad, respectively) about project quality before making loans. The signal is always good ($s = g$) when the borrower is a good type while the signal is bad ($s = b$) with probability $\theta \in [0,1]$ when the borrower is a bad type. In other words, if the fintech lender defines a borrower being good as the null hypothesis in the screening process, the signal makes a Type II error (false negative) with probability $1 - \theta$ and makes no Type I errors (false positive) .

The lender chooses $\theta \in (0,1)$ at a convex cost $c(\theta)$ where $c'(\theta) > 0$, $c'(0) \to \infty$, and $c''(\theta) > 0$. Therefore, θ can be interpreted as the fintech lender's investment in screening technology, or

[5] We can assume the measure of fintech lenders is larger than 2, so the number of lenders is larger than the largest possible number of investment projects that are waiting to be financed at every date.

equivalently, its screening effort. An alternative way to model the screening cost is to assume that the borrower also generates a flow disutility $d(\theta)dt$ per dt unit of time, where $d(\theta)$ is increasing and convex in the screening effort. This disutility term captures the borrower's concern about data privacy. The main results of the paper are robust even when we introduce such concern about data privacy. Therefore, we interpret the screening cost in the model more broadly as the combination of the fintech lender's investment for screening with alternative data and the borrower's disutility over data privacy.

In contrast, we assume banks have no access to such a screening technology, so they can only make loan decisions based on π, the publicly observable quality of the borrower. Therefore, the screening technology in the model can be interpreted as the fintech lender's ability to develop machine learning tools or alternative data pipelines in evaluating borrower quality.[6] For instance, the Ant Financial Group, a bigtech lender in China, can utilize consumers' online shopping records when screening their consumer loan applications, and can also extract information from online retailers' sales history when screening their business loan applications (Netzer et al. 2019). In this example, commercial banks are unable to adopt the advanced screening technology, simply because they have no access to those alternative data (Djeundje et al., 2021). In addition, banks are lagging behind in screening with alternative data because of their slow adoption of financial technology and their conservativeness regarding data privacy violations (Stulz 2019).

In order to study the value of fintech lenders' credit history data and the effect on potential fintech-bank collaborations, we focuses on the group of borrowers that have no access to financing from the traditional banking sector. Specifically, we assume that banks find it too risky to lend to borrowers in the model, or equivalently,

Assumption 2. *$\pi < \pi_b$, where $\pi_b \frac{y+\lambda+b}{\rho+\lambda} + (1-\pi_b)\frac{y+\lambda+b}{\rho+\lambda+\eta} < 1$.*

In practice, there are reasons why some borrowers are underserved by traditional banks. First, small and medium enterprises may lack sufficient collateral assets, which are sometimes required

[6] For example, Duarte et al. (2012) show using psychometrics that people who appear more trustworthy have better credit scores and Berg et al. (2020) shows a credit application's digital footprints are informative of credit quality.

for business loans (Cole and Sokolyk, 2016). Second, borrowers with low credit scores and limited credit history may be denied credit by banks due to a lack of data to evaluate their creditworthiness. For these borrowers, fintech lenders can reduce lending risks for these high-risk borrowers by using alternative data for screening, improving their access to financing.[7] Hereinafter, we focus on parameter restrictions where underserved borrowers apply for loans from fintech lenders.

The Lending Market

In the lending market, the representative borrower observes a list of interest rates quoted by fintech lenders. For simplicity, we restrict the attention to fixed-rate non-amortizing loans. Specifically, each loan has a principal amount of 1, and is associated with an interest rate R. After the initial lending, the borrower pays Rdt to the lender per unit of time. The interest rate cannot exceed the project's cashflow y, otherwise the borrower is unable to make interest payments, which would lead to immediate default. When the borrower's project matures, the borrower repays the principal value of the loan. When the project fails, the lender recovers zero from the loan. The loan contract in the model does not have a deterministic maturing date, so it is interpreted as a credit line to corporate firms or a consumer loan to households.

After observing all the interest rates offered in the lending market, the borrower chooses to apply a loan from one fintech lender. The lender chooses to screen the borrower with effort level θ. If receiving a bad signal, the fintech lender learns that the borrower has a bad project and will reject its loan application. If receiving a good signal, the lender's posterior belief about the borrower's credit quality improves, and the lender lends to the borrower at the quoted interest rate. Denote the fintech lender's lending rate by R. To simplify the analysis, we make the following assumption:

Assumption 3. $y < \rho_b$

Under Assumption 2, good-type borrowers find it optimal to immediately consume the net

[7] For example, Square Capital - the lending arm of the Square payment processor - has a page titled "Expanding Access" with statistics on how it has made loans to small businesses typically underserved by banks. See https://squareup.com/us/en/capital/access, accessed November 2023.

income (or pay out as dividend), instead of using it to pay down the loan in advance. Bad-type borrowers have no choice but to mimic the behavior of good-type borrowers, otherwise they will be recognized as bad-type borrowers and their projects would be foreclosed.

Timing

The timing of the model is the follows.

1. At date t_0, fintech lenders quote interest rates to compete in the lending market.

2. The borrower chooses to apply a loan from only one fintech lender. Upon receiving a loan application, a fintech lender first chooses the screening effort θ and then decides whether to accept or reject the application based on the borrower's observable quality and the screening signal.

3. If the loan application is approved, the lender lends to the borrower at the quoted interest rate R. The lender receives the interest payment over time, until the project matures or fails.

2.2 Fintech Lending

Now we solve for the fintech-lending equilibrium where fintech lenders provide financing to these borrowers that are underserved by banks. We focus on pooling equilibrium where good-type and bad-type borrowers choose to apply loans from fintech lenders that offer the same contract in the lending market. Due to the assumption that bad-type borrowers' projects are negative NPV, they will always mimic the behavior of good-type borrowers in order to obtain financing in the lending market. In such a pooling equilibrium, each fintech lender's objective is to minimize the interest rate offered to the market, subject to a break-even constraint. To see this, note that a good-type borrower can always obtain a loan from a fintech lender, because the lender's screening signal makes no type-I errors. Therefore, among all fintech lenders, good-type borrowers would choose to apply loans from those who provide the lowest-possible interest rate, and bad types borrowers would do so too in order to mimic the behavior of good-type borrowers. In other words, each fintech lender chooses the interest rate R and screening effort θ to minimize the interest rate offered to the market, or equivalently,

$$\begin{aligned} \underset{\theta\in[0,1]}{min}\ R \quad \text{subject to} && (1) \\ c(\theta) \leq \pi(\frac{R+\lambda}{\rho+\lambda}-1)+(1-\pi)(1-\theta)(\frac{R+\lambda+\eta L}{\rho+\lambda+\eta}-1) && (2) \end{aligned}$$

Equation 2 is the break-even constraint, which requires the fintech lender to earn a non-negative profit from making the loan. In the break-even constraint, the fintech lender screens the borrower at a cost $c(\theta)$. With probability $(1-\pi)\theta$, the screening signal is bad, in which case the fintech lender rejects the loan application. With probability $\pi+(1-\pi)(1-\theta)$, the fintech lender receives a good signal and updates its posterior belief about the borrower being of good type from π to $\frac{\pi}{\pi+(1-\pi)(1-\theta)}$. In this case, the fintech lender lends to the borrower at the interest rate R.

Denote the solution to the minimization problem 1 by (R^*,θ^*). The equilibrium interest rate and screening effort must satisfy

$$\begin{aligned} c'(\theta^*) &= (1-\pi)[1-\frac{R+\lambda+\eta L}{\rho+\lambda+\eta}] && (3) \\ c(\theta^*)+c\text{'}(\theta^*)(1-\theta^*) &= \pi[\frac{R+\lambda}{\rho+\lambda}-1], && (4) \end{aligned}$$

the equilibrium screening effort and face value (R^*,θ^*) are uniquely pinned down by the lender's optimality condition (Equation 3) and break-even condition (Equation 4).[8] The lender's optimality condition implies a negative relation between the face value and the screening effort. Intuitively, an increase in the interest rate reduces the expected loss of making a loan to a bad project, thereby reducing the fintech lender's incentive to screen. In contrast, the lender's break-even condition

[8]The above two equations give the interior solution to the problem. Depending on parameter values, a corner solution with $\theta^*=1$ may arise. Throughout the paper, we focus on parameter values that lead to a interior solution for fintech screening.

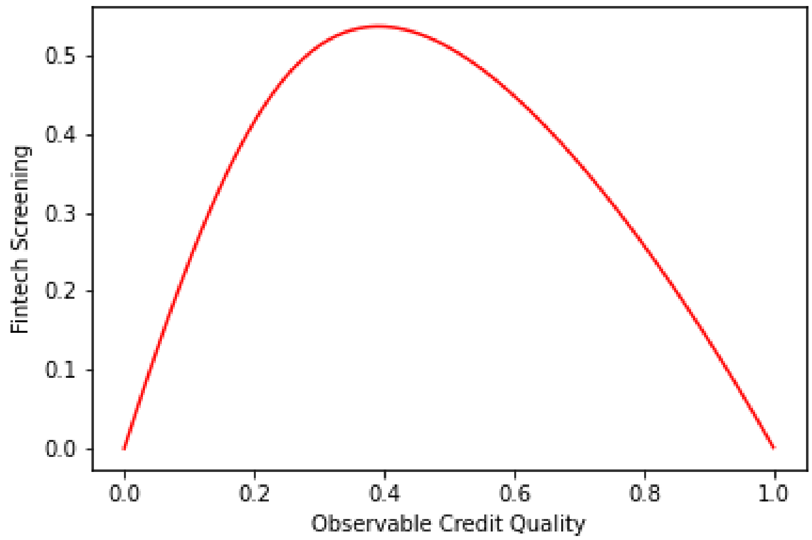
implies a positive relation between the face value and the screening effort. An increase in the screening effort increases the fintech lender's total lending cost, which is the sum of the screening cost $c(\theta^*)$ and the expected loss of making loans to a bad project $c'(\theta^*)(1-\theta^*)$, thereby inducing the fintech lender to charge a higher face value to break even. In sum, the solution to the minimization problem 1 is unique. However, the fintech lender is active in the lending market if and only if the interest rate R^* does not exceed y, the cashflow from the borrower's project. Proposition 1 formally states the fintech-lending equilibrium

Proposition 1. *There exists a threshold value π_f such that fintech lenders are active in the lending market if $\pi \in [\pi_f, \pi_b)$. π_f is strictly smaller than π_b when $b < \bar{b}$and $y \in (y_1, y_2)$. When fintech lenders are active in the lending market, the equilibrium screening effort and interest rate (θ^*, D^*) are the unique solution of equations (3) and (4).*

π_b is the lowest quality of any borrower to whom a bank would provide financing. Fintech lenders are able to provide financing to some borrowers that are underserved by banks if $\pi_f < \pi_b$ holds with strict inequality. Proposition 1 shows this inequality holds under certain parameter conditions. Firstly, the funding-cost advantage of banks b must be relatively small. When b is too large, the fintech lender's screening advantage is overwhelmingly dominated by its disadvantage in funding costs, making it impossible for fintech lenders to improve financial inclusion. Secondly, the cashflow from the project, which reflects the borrower's ability to service its debt, must stay in an intermediate range (y_1, y_2). To understand this result, we first introduce the following corollary

Corollary 1. *In a fintech-lending equilibrium, the equilibrium screening effort θ^* is non-monotonic in the borrower's observable quality π. Specifically, there exits a threshold value π_T such that $\frac{d\theta^*}{d\pi} > 0$ if $\pi < \pi_T$ and $\frac{d\theta^*}{d\pi} < 0$ otherwise.*

Figure 1: Credit Quality and Fintech Screening



As stated in Corollary 1 and shown in Figure 1, the screening effort is a hump-shaped function of the borrower's observable quality of the borrower. Intuitively, an increase in π has two effects on the marginal screening benefit, which is $(1-\pi)[1-\frac{R+\lambda}{\rho+\lambda+\eta}]$, the right hand side of equation (3). First, it directly reduces the marginal screening benefit, as an improvement in the borrower's observable quality makes private information production less important. Second, an increase in π reduces the lending rate R, which increases the marginal screening benefit by raising the expected cost of making a bad loan. The latter effect dominates when π is relatively small, resulting in a positive relation between fintech screening and borrower observable quality for high-risk borrowers, while the former effect dominates when π is relatively large, resulting in a negative relation between fintech screening and borrower observable quality for low-risk borrowers. In other words, a fintech lender's screening advantage is the largest when servicing borrowers with intermediate levels of credit risks.

Given Corollary 1, let's explain why fintech lenders can improve financial inclusion by financing borrowers that are underserved by banks only when $y \in (y_1, y_2)$. When $y < y_1$, borrowers do not have many cashflows to service their debt, so only borrowers with high observable quality will be financed. For these borrowers, fintech lenders' screening advantages over banks are relatively low, so they are unable to compete with banks in the lending market. When $y > y_2$, borrowers have plenty of cashflows to service their debt, so even borrowers with low observable quality will be financed by banks. Those borrowers that are underserved by banks have high credit risks. For these borrowers, fintech lenders' screening advantages over banks are also low, so they are unable to improve financial inclusion neither.[9] However, when $y \in (y_1, y_2)$, banks find it too risky to lend to borrowers with intermediate levels of credit quality, whereas fintech lenders may extend credits to these borrowers for whom the fintech screening advantage is the largest. This result suggests that fintech lenders improve financial inclusion for borrowers with intermediate levels of cashflows that can be used for debt payment. For borrowers with low cashflows and high default risks, fintech lenders may be outcompeted by banks because their screening technologies have little value-added. Corroborating this theoretical result, finds that small business lending (which comprises more than 70% of borrowing) did not recover to the same amoutn compared to larger loans after the financial crisis. They also find that fintech lenders filled the gap by increasing lending to that group of borrowers.

Our model suggests a non-trivial relationship between public information provision and private screening effort, because the information "crowd-in" effect may seem counterintuitive. Corollary 1 indicates that increasing public information provision, which enhances the borrower's observable credit quality (given a positive public signal), may either stimulate or suppress private information production through screening. This result also suggests policymakers seeking to provide incremental information to the public on borrowers, such as the availability of corporate financial statements, ownership structures, and other disclosures, should be mindful of the current information environment. In developed countries where disclosure requirements are extensive, providing incremental information may discourage investments in financial screening technology. On the other hand, in emerging countries with limited public data, government investment in information infrastructure can "crowd in" and encourage further private information production.

[9]While fintech lenders do not improve financial inclusion in this case, they may compete with banks and take some borrowers away from banks, especially those borrowers with intermediate levels of credit quality. A rigorous analysis of lending market competition is beyond the scope of the paper.

2.3 Credit History Data

As the fintech lender screens and lends to a borrower, she also obtains information about the borrower, including the initial screening signal and information about whether the borrower has defaulted on the loan. These pieces of information will be referred to as the borrower's credit history data. A borrower's credit history data can be summarized by three variables $\Phi_t = (t - t_0, i_s, i_{d,t})$, where $t - t_0$ denotes the time interval between the date when the borrower applied for a loan and the current date, $i_s \in \{0, 1\}$ denotes whether the borrower has passed the initial fintech screening, and $i_{d,t} \in \{0, 1\}$ denotes whether the borrower has defaulted on the loan in the past. To simplify the analysis, we assume that whether the borrower's project is matured or not, that is, whether the borrower needs financing at the current moment, is public information. We call that a borrower has good credit history at date t if the borrower passes the initial fintech screening ($i_s = 1$) and has not defaulted yet ($i_{d,t} = 0$).

The value of credit history data changes dynamically. Conditioning on the fact that the borrower has not defaulted on the loan, the fintech lender's posterior belief about the borrower's credit quality improves over time. This result is driven by the assumption that a bad-type borrower defaults at a higher poisson rate than a good-type borrower does. We use π_τ to denote the lender's belief about the probability that the borrower is of good type conditioning on that the borrower has not defaulted for τ units of time. Then π_τ evolves as $d\pi_\tau = \eta \pi_\tau (1 - \pi_\tau) d\tau$, with $\pi_0 = \frac{\pi}{\pi + (1-\pi)(1-\theta)}$. We have $\pi_\tau = \frac{\pi}{\pi + (1-\pi)(1-\theta)e^{-\eta\tau}}$, which is an increasing function on τ.

In the fintech lending equilibrium, we assume that the borrower's credit history data is privately owned by its lender. If the borrower's credit history data becomes publicly available, and assuming the borrower does not default on the loan, its perceived creditworthiness improves. This gives the borrower an incentive to search for another lender in order to obtain a lower borrowing rate. If the cost of searching and switching lenders is relatively low, the initial lender cannot profit from the lending relationship. As a result, the initial lender may have little motivation to screen the borrower, leading to credit rationing.

Therefore, we primarily focus on the scenario where the fintech lender owns the borrower's credit history data. Under this assumption, although the lender's belief about the borrower's credit quality improves over time, the borrower's credit history data remains confidential and not publicly known. In that case, the lender has no incentive to adjust the interest rate[10] and is able to capture information rents due to her private data ownership. Because fintech lenders possess valuable credit history data, there is gain from trade for fintech lenders to collaborate with traditional banks or other low-funding-cost financiers. Such a fintech-bank collaboration combines a fintech lender's screening advantage with a bank's low funding cost. In the next section, we study the impact of introducing fintech-bank collaborations under various contractual and regulatory environments and discuss their welfare implications.

3 Fintech-Bank Collaborations

By lending to ex ante risky borrowers rationed by banks, fintech lenders create valuable credit history data, which is valuable to banks in making lending decisions. In this section, we study how fintech-bank collaborations under different contractual environments affect fintech screening and borrowing rates in the economy. A fintech-bank collaboration requires both the fintech lender's screening skill and the bank's low-cost funding. If there are no contractual frictions, the bank would fund the loan to the borrower while the fintech lender screens at the optimal level that balances marginal benefit and cost. We introduce two additional assumptions to make the interaction between fintechs and banks more realistic.

First, we assume that fintechs and banks cannot contract on the screening effort of the fintech lender. In reality, the screening costs incurred may include the development of machine learning models and hiring of data scientists that may not be observable to external parties. This assumption also effectively prevents the bank from acquiring the fintech lender, as such an acquisition would make the screening effort controllable by the bank. With this assumption in mind, the fintech lender in our model is better understood as bigtech companies like Google, Apple, or Ant Financial

[10] The borrower's outside option of not borrowing from the current lender is to find another fintech lender who is uninformed of her credit history. In that case, the new lender would offer the same interest rate as the borrower gets from the current lender. As a result, neither a good-type nor a bad-type borrower has an incentive to borrower from a new lender were there a tiny cost of searching and switching.

Group, which may either be too large and complex to be acquired by traditional banks.[11] Second, we assume that the fintech lender is protected by limited liability. Under this assumption, the bank cannot force the fintech lender to cover its losses in the event of a default on a fintech-related loan.[12] Under these two assumptions, the only way to incentivize fintech screening is for the fintech lender to have skin in the game by financing a certain amount to the fintech loan or finance the loan for a certain period of time.

To study the fintech-bank collaboration, we revise the timing of the model slightly:

1. At date 0, the fintech lender and bank enters into a collaboration contract. Then, the fintech lender quotes an interest rate in the lending market to the ex ante risky borrowers.[13]

2. At date t_0[14], the fintech lender receives a loan application, she first chooses the screening effort θ and then decides whether to accept or reject the application based on the borrower's observable quality and the screening signal. If the loan application is approved, she lends to the borrower at the quoted interest rate R.

3. At date t_1, the fintech lender contacts the bank to execute the collaboration contract. Different types of collaboration contracts will be introduced in the next few subsections.

Although the bank and fintecher agree upon a contract (like signing a binding MOU or termsheet), the fintech lender can choose when to initiate the collaboration based on those terms. Note thatsuch a collaboration does not affect the interest rate R the borrower pays, because the borrower's credit

[11]While our framework focuses on the lending function within these bigtech companies, in practice due to the non-rivalrousness of data (Jones and Tonetti 2020), the data generated by the bigtech is likely not only used for the borrower screening function and may be used for other things like targeted ads. These other revenue streams by the data generator also makes acquisition of the fintech lender untenable, so we believe this assumption is realistic.

[12]If the fintech lender is allowed to compensate the bank when the fintech loan defaults, the optimal contract would trivially have the fintech lender bear all the lending risks and the bank make a risk-free loan to the fintech lender. Another way to rationalize this assumption is that if the bank lends to the fintech lender, the lending is subject to a stringent capital requirement that eliminates the bank's funding-cost advantage.

[13]To give an example, Square advertises its loans and rates as a banner to entice potential borrowers to apply for a loan. For example, see the example Square loan marketing snippet https://www.business.org/finance/loans/square-capital-review/, accessed November 2023.

[14]We assume date t_0 is relatively distant from date 0 is a random variable with sparse distribution. This assumption means the bank cannot use the length of the time interval between 0 and t_1 to infer much information about the borrower's credit quality.

history is privately owned by the fintech lender and the collaborating bank, who are able to capture information rents by keeping the interest rate unchanged even when the borrower's credit quality improves over time (conditional on no defaults).

Below, we show that the optimal fintech-bank collaboration depends crucially on whether the borrower's credit history data is contractable or not, that is, whether payment can be contingent on the borrower's credit history data.[15] When credit history data are not contractable, the optimal contract analyzed in Section 3.1 is an joint lending contract where the fintech lender and the bank jointly lend to the borrower. When credit history data are contractable, the optimal contract analyzed in Section 3.2 is a data selling contract where the fintech lender sells the borrower's credit history data to the bank. Section 3.3 compares different types of contracts, highlighting the role of financial technology in affecting the relationship between fintech lenders and banks.

3.1 Joint Lending

First, we analyze the case where the borrower's credit history data is not contractable. In this case, a fintech-bank collaboration contract specifies two variables $\{\alpha, P\}$: α captures the fintech lender's share of the loan and P captures the one-time service fee paid from the bank to the fintech lender at date t_1, which we interpret as the price of the credit history data. We assume that the fintech lender and the bank receive interest and principal payments that are proportional to their initial loan contributions and in determining the service fee, we assume the fintech lender has all the bargaining power over the bank. For now, we also assume the recovery value of a failed project is assumed to be zero, so there is no need to split that recovery value between the two lenders. Later, we will discuss the case when the recovery value is positive.

Because whether the borrower exits the economy is public information, the bank would pay P only when the borrower' project has not matured at date t_1. We first establish a lemma about the shape of the optimal collaboration contract.

Lemma 1. *In the optimal contract, the fintech lender chooses $t_1 = t_0$, so that she executes the*

[15] For example, we interpret the recent innovations in financial technology enabling data tokenization and the certification of data generation to tokenization process by third-party code auditors as making the data contractable.

collaboration contract immediately after receiving a borrower's loan application.

Under the optimal contract, the fintech lender begins the collaboration immediately after receiving a borrower's loan application, rather than lending to the borrower for a certain period of time before collaborating with the bank. To see this, imagine that the bank expects the fintech lender to lending to the borrower for τ units of time and then executes the collaboration contract. If the fintech lender indeed does so, its expected value at date t_0 (the time when she receives the borrower's loan application) is

$$W(\tau) = -c(\theta) + (\pi + (1-\pi)(1-\theta))(V(t = t_0; \theta, R, \alpha, P, \tau) - 1) + e^{-(\rho+\lambda)\tau}P.$$

The last term $e^{-(\rho+\lambda)\tau}P$ is the present value of service fee from fintech-bank collaboration. In this case, the service fee cannot be contingent on the borrower's credit history. $V(t_0) = V(t = t_0; \theta, R, \alpha, P, \tau)$ is the date-t_0 expected value of interest and principal payments from the loan, given that the fintech lender executes the collaborating contract (α, P) at date $t_0 + \tau$, and $V(t)$ solves the following ordinary differential equation (ODE):

$$\rho V = R + \lambda(1-V) + \eta \frac{(1-\pi)(1-\theta)e^{-\eta(t-t_0)}}{\pi + (1-\pi)(1-\theta)e^{-\eta(t-t_0)}}(0-V) + \frac{dV}{dt},$$

with the boundary condition that $V(t_0+\tau) = (1-\alpha) + \alpha[\frac{R+\lambda}{\rho+\lambda}\pi_\tau + \frac{R+\lambda}{\rho+\lambda+\eta}(1-\pi_\tau)]$, where $\pi_\tau = \frac{\pi e^{\eta\tau}}{\pi e^{\eta\tau}+(1-\pi)(1-\theta)}$ is the borrower's credit quality conditional on the borrower has good credit history at date $t_0+\tau$. The left hand side of the equation is the fintech lender's required return for lending to the borrower for the first τ unit of time. On the right hand side, the first term is the interest payment from the borrower. The second term captures the expected value change due to project maturity. The third term is the expected value change due to project failure, note that the poisson rate of project failure is the product of the failure rate of a bad project η and the perceived probability of the project being of bad type $\frac{(1-\pi)(1-\theta)e^{-\eta(t-t_0)}}{\pi+(1-\pi)(1-\theta)e^{-\eta(t-t_0)}}$, which is gradually decreasing as the borrower accumulates a longer period of good credit history. The fourth term captures the time-varying nature of the value function.

Solving the ODE, we can write the borrower's total expected value from the lending as

$$W(\tau)=\begin{array}{c}-c(\theta)+e^{-(\rho+\lambda)\tau}P+\pi(\frac{R+\lambda}{\rho+\lambda}-1)(1-(1-\alpha)e^{-(\rho+\lambda)\tau})+\\ (1-\pi)(1-\theta)(\frac{R+\lambda}{\rho+\lambda+\eta}-1)(1-(1-\alpha)e^{-(\rho+\lambda+\eta)\tau}).\end{array} \tag{5}$$

The service fee P is determined by the bank's participation or break-even constraint, that is,

$$P=(1-\alpha)[\pi(\frac{R+\lambda+b}{\rho+\lambda}-1)+(1-\pi)(1-\theta)(\frac{R+\lambda+b}{\rho+\lambda+\eta}-1)e^{-\eta\tau}]. \tag{6}$$

Because τ is a part of the borrower's credit history data that cannot be written into the contract, the fintech lender is choosing τ, the optimal time to execute the fintech-bank collaboration, while taking the service fee P as given. In this case, we can show that $\frac{\mathrm{dW}(\tau)}{d\tau}<0$ for all $\tau>0$. In other words, when the bank expects the fintech lender to execute the fintech-bank collaboration contract τ units of time after the initial borrowing, the fintech lender always can profitably deviate by executing the contract earlier. Such a profitable deviation occurs because the value of credit history data increases with the length of the borrower's good credit history. Since the length of the borrower's credit history cannot be contracted, the fintech lender always has an incentive to collaborate with the bank at an earlier stage. Thus, the only rational expectation equilibrium is for the fintech lender to execute the collaboration contract immediately after receiving the borrower's loan application.

In summary, when the borrower's credit history data is not contractable, the optimal collaboration contract between the fintech lender and the bank involves jointly lending to a borrower who passes fintech screening.The joint lending contract encourages screening efforts by allowing the fintech lender to hold a portion of the loan.

Now we discuss the case when the recovery value of a failed project is positive. In this case, the collaboration contract must specify how the fintech lender and the bank will divide the recovery value. Our analysis suggests that the optimal collaboration contract should not provide the lowest-possible recovery value to the fintech lender in default. Reducing the fintech lender's recovery value from a failed project creates a higher incentive for the fintech lender to exert screening effort, allowing to the fintech-bank collaboration to provide a more competitive interest rate to borrowers. Therefore, when the recovery value is positive, the joint lending contract resembles securitized product like in an asset-backed security (ABS), where the fintech lender lends to a borrower and sells the senior tranche of the loan to a bank. In practice, we observe similar arrangements in China, where the Ant Group packages consumer loans and business loans into asset-backed securities (ABS) and sells senior tranches of these ABS to commercial banks and other institutional investors. This kind of securitization is also similar to the asset back securities market (Carbo-valverde et al., 2015).

Now we solve for the optimal joint lending contract. At date t_0, the fintech lender chooses (R,θ) to minimize the lending rate, taking the collaboration contract (α,P) as given. $R=R(\alpha,P)$ and $\theta=\theta(\alpha,R)$ solves

$$
\begin{aligned}
c'(\theta) &= \alpha(1-\pi)[1-\frac{R+\lambda}{\rho+\lambda+\eta}] &(7)\\
c(\theta)+c'(\theta)(1-\theta) &= \alpha[\pi(\frac{R+\lambda}{\rho+\lambda}-1)+(1-\pi)(1-\theta)(\frac{R+\lambda}{\rho+\lambda+\eta}-1)]+P &(8)
\end{aligned}
$$

The optimal collaborating contract (α^*,P^*) solves

$$
\begin{gathered}
\min_{\alpha\in[0,1],P\geq 0} R(\alpha,P) \quad \text{subject to} \\
P\leq(1-\alpha)[\pi(\frac{R(\alpha,P)+\lambda+b}{\rho+\lambda}-1)+(1-\pi)(1-\theta(\alpha,P))(\frac{R(\alpha,P)+\lambda+b}{\rho+\lambda+\eta}-1)].
\end{gathered}
$$

Proposition 2 states properties of the optimal joint lending contract.

Proposition 2. *When the borrower's credit history data is not contractable, the optimal collaboration contract is an joint lending contract where the fintech lender sells a fraction of the loan to the bank at date t_0. Denote the fintech loan share, the fintech screening effort, and the interest rate under the optimal joint lending contract by $\alpha^*,\theta_{JL},R_{JL}$, respectively.*

3.2 Data Selling

In this section, we study the optimal fintech-bank collaboration contracts when the borrower's credit history data $\Phi_t = (t - t_0, i_s, i_{d,t})$ is contractable in the sense that it can be credibly transferred from the fintech lender to the bank. Now, the data-selling price can depend on the borrower's credit history. We first restrict our attention to contracts where the data price only depends on $t - t_0$, the time interval between the date when the borrower applied for a loan and the current date. Section 4.2 discusses the other case where the contract can also be contingent on the borrower's screening result i_s and default history $i_{d,t}$.

In this setting, a fintech-bank collaboration contract specifies $\{\alpha, P, \tau\}$: α captures the fintech lender's share of the loan, P captures the one-time service fee paid from the bank to the fintech lender at date $t_1 = t_0 + \tau$, and τ is the time length of fintech lending. At date t_1, the bank pays the service fee P if the borrower' project has not matured at date t_1. We first establish a lemma about the shape of the optimal collaboration contract in this case.

Lemma 2. *In the optimal contract, $\alpha = 0$, so that the bank provides all the funding after the fintech lender executes the collaboration contract.*

Intuitively, when the borrower's credit history data is contractable, the collaboration contract can induce fintech screening through two channels. First, it can induce fintech screening by having the fintech contribute more to the loan (α). Second, it can induce fintech screening by having the fintech lender hold the loan for longer (τ). Note that the latter channel is only available when τ becomes contractable. In the model, it is more effective to provide fintech screening via the second channel because the borrower's credit quality improves over time conditional on no defaults. In other words, the likelihood of default is higher for the initial lending period. Comparing to the fintech lender holding a fraction of the loan for all future periods, the fintech lender holding the loan for the first τ period of time can provide screening incentive more efficiently. As a result, the optimal contract features $\alpha = 0$.

When the borrower's credit history data is contractable, the optimal fintech-bank collaboration contract can be implemented by the fintech lender lending to a borrower for a period of time and then transferring the borrower's credit history data to the bank. Then, the bank lends 1 dollar to the borrower (at the same interest rate as the fintech loan's) for her to repay her fintech loan. The bank is willing to do this because the borrower has good credit history, that is, the borrower passed the fintech screening and hasn't defaulted yet. We will refer to this type of fintech-bank collaboration as a *data selling* contract. The data selling contract incentivizes fintech screening by having the fintech lender hold the loan for the initial period of lending.

Now we solve for the optimal data selling contract. At date t_0, the fintech lender chooses (R, θ) to minimize the lending rate, taking the collaboration contract $(\alpha = 0, P)$ as given. $R = R(\tau, P)$ and $\theta = \theta(\tau, P)$ solves

$$c'(\theta) = (1 - e^{-(\rho+\lambda+\eta)\tau})(1-\pi)[1 - \frac{R+\lambda}{\rho+\lambda+\eta}] \tag{9}$$

$$c(\theta) + c'(\theta)(1-\theta) = \begin{array}{c} e^{-(\rho+\lambda)\tau}P + (1 - e^{-(\rho+\lambda)\tau})\pi(\frac{R+\lambda}{\rho+\lambda} - 1) + \\ (1 - e^{-(\rho+\lambda+\eta)\tau})(1-\pi)(1-\theta)(\frac{R+\lambda}{\rho+\lambda+\eta} - 1). \end{array} \tag{10}$$

The optimal collaborating contract (τ^*, P^*) solves

$$\min_{\tau \geq 0, P \geq 0} R(\tau, P) \quad \text{subject to}$$

$$P \leq \pi(\frac{R(\tau,P)+\lambda+b}{\rho+\lambda} - 1) + e^{-\eta\tau}(1-\pi)(1-\theta(\tau,P))(\frac{R(\tau,P)+\lambda+b}{\rho+\lambda+\eta} - 1).$$

In fintech-bank collaboration under data selling contracts, fintech lenders serve as an on-ramp to the financial system by lending to risky borrowers for the first τ^* period of time and then selling borrowers' credit history data to banks, who take over subsequent lending. Proposition 3 states properties of τ^* in the optimal data selling contract.

Proposition 3. *When the borrower's credit history data is contractable, the optimal collaboration* *contract is a data selling contract where the fintech lender lends to the borrower for τ^* units of time and then sells the borrower's credit history data to the bank. The time length of fintech lending in the optimal contract τ^* has the following properties: $\frac{\partial \tau^*}{\partial b} < 0$, and there exits a π_1 such that $\frac{\partial \tau}{\partial \pi} \leq 0$ if and only if $\pi > \pi_1$.*

Proposition 3 states a few predictions about how the time length of fintech lending in the optimal contract varies with model parameters, which are also plotted in Figure 1. First, an increase in the bank funding advantage (b) reduces the time length of fintech lending (τ^*), because an increase in bank funding advantage raises the marginal benefit of relying on bank funding. Second, the time length of fintech lending is the highest when π, the observable credit quality of borrowers, take an intermediate value. The intuition of this result is similar as in Proposition 2. The optimal fintech screening is the highest for borrowers with intermediate levels of observable credit quality. Consequently, the time length of fintech lending in the optimal data selling contract also inherits that non-monotonicity property, because the data selling contract incentivizes fintech screening solely by having the fintech lender hold the loan for the initial period of time.

Denote the fintech screening effort and interest rate under the optimal data selling issuance contract by (θ_{DS}, R_{DS}). We will compare these variables under different contractual environments in Section 3.3.

3.3 Contract Comparisons

Now we compare screening efforts and interest rates under three different types of contractual environments, the economy without fintech-bank collaboration (θ^*, R^*) , the economy where borrowers' credit history data is not contractable (θ_{JL}, R_{JL}), and the economy where borrowers' credit history data is contractable (θ_{DS}, R_{DS}). Proposition 4 summarizes the comparison of screening efforts and interest rates under different contractual environments.

Proposition 4. *$R_{DS} < R_{JL} < R^*$. There exists a B_1 such that $\theta_{JL} < \theta_{DS} < \theta^*$ if $b > B_2$ and $\theta_{DS} \leq \theta_{LS} < \theta^*$ otherwise.*

Figure 2: The Effects of Bank Funding Advantage

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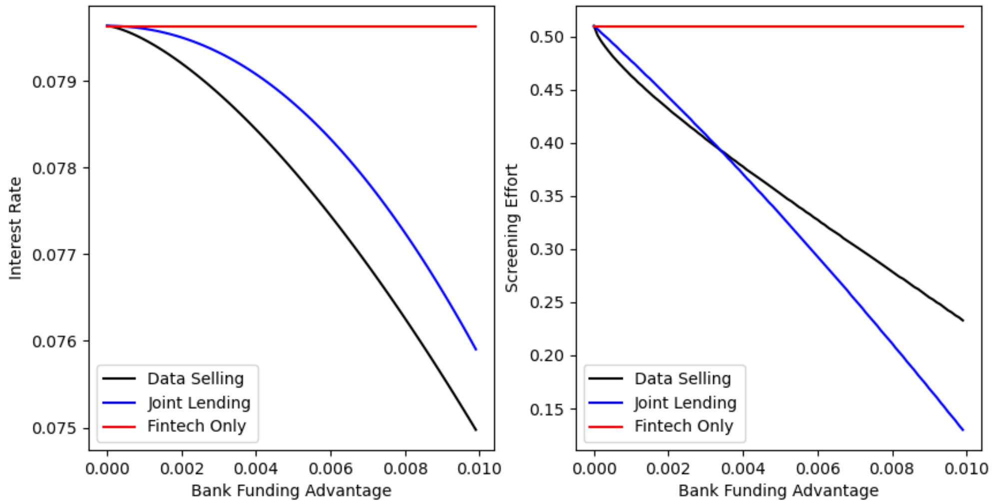


Figure 2 compares of optimal contracts under different contractual environments. Comparing the economy without fintech-bank collaboration to the other two economies that allow for fintech-bank collaboration, we find that introducing fintech-bank collaborations decreases the borrowing rate and the fintech screening effort. The decrease in the borrowing rate is not surprising, because allowing fintech-bank collaborations reduces the lender's effective funding cost, leading to more financial inclusion, as some risky borrowers who are not financed by fintech lenders are able to obtain funding in the economy with fintech-bank collaborations.

Introducing fintech-bank collaborations also reduces the fintech lender's screening effort. When we allow for fintech-bank collaboration, fintech screening is incentivized either by the fintech lender contributing a certain fraction of the loan amount (as in the joint lending contract) or by the fintech lender holding the loan for a certain period of time (as in the data selling contract). In both cases, the optimal collaboration contract must require the fintech lender to contribute some funding so as to induce a proper screening effort. So when we allow fintech-bank collaboration, the marginal cost of screening becomes higher as it now contains the opportunity costs of the funding-cost subsidy that could have been earned by relying more on bank funding. Therefore, introducing fintech-bank collaboration lowers the fintech screening effort.

We compare the two economies with different assumptions about the contractability of borrowers' credit history data. Proposition 4 shows that when credit history data becomes contractable, the borrowing rate in the economy decreases. When credit history data is not contractable, the optimal contract incentivizes fintech screening only with the contribution fraction α. However, when credit history data becomes contractable, the collaboration contract can also incentivize fintech screening by having the fintech lender to hold the loan for the initial period of time (τ). The latter channel is more efficient in inducing screening effort than the former one,so making credit history data contractable results in lower borrowing rates in the economy. In other words, when credit history data is contractable, the data selling contract dominates the joint lending contract, because it induces fintech screening more efficiently, thereby allowing the fintech lender to offer a lower interest rate in the lending market.

However, how the screening effort changes with the introduction of data contracting technology is theoretically ambiguous. On the one hand, compared to the joint lending contract, the data selling contract is more efficient in inducing the screeing effort. All else being equal, the data selling contract should lead to a higher level of fintech screening. On the other hand, the interest rate under the data selling contract is lower than that under the joint lending contract. So, the marginal screening benefit, which is proportional to the fintech lender's loss of making a bad loan, is lower under the data selling contract. Due to this interest rate difference, the fintech lender has a lower incentive to screen under the data selling contract. Because of the two opposite effects, the screening effort comparison is ambiguous. Figure 2 shows how the screening effortchanges depends crucially on the bank's funding advantage. Compared to the joint lending contract, the data selling contract generates a lower screening effort when the bank's funding advantage is small and a higher screening effort when the bank's funding advantage is relatively large. This result suggests that making credit history data contractable in fintech-bank collaborations induces more investments in screening technology if traditional banks enjoy large funding-cost advantages.

3.4 Policy Implications

While the fintech lender in the private economy prefers to collaborate with a bank in the lending market, whether fintech-bank collaboration leads to a higher social welfare is ambiguous. To analyze the welfare implication of the model, we need to introduce a social planner in the economy without fintech-bank collaboration.

The social planner is uninformed of the borrower's private type but can dictate the fintech lender's choice of screening effort θ.[16] As such, the social planner chooses θ to maximize the expected payoff of the representative borrower, that is,

$$\max_{\theta\in[0,1]} \pi\frac{y-R(\theta)}{\rho_b+\lambda}+(1-\pi)(1-\theta)\frac{y-R(\theta)}{\rho_b+\lambda+\eta},$$

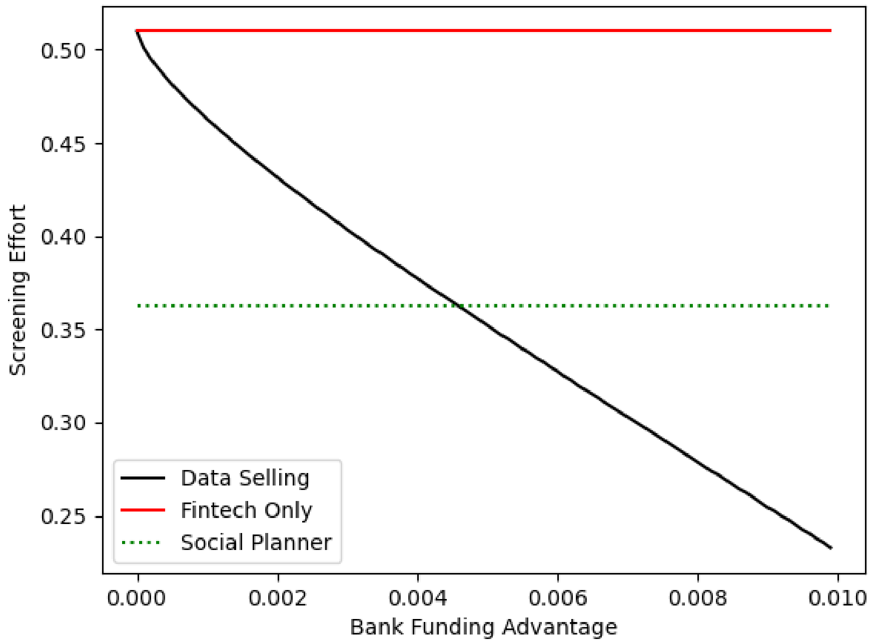
where $R(\theta)$ is the break-even interest rate the fintech lender charges such that $c(\theta)=\pi(\frac{R(\theta)+\lambda}{\rho+\lambda}-1)+(1-\pi)(1-\theta)(\frac{R(\theta)+\lambda}{\rho+\lambda+\eta}-1)$. Denoting the social planner's choice of fintech screening effort by θ_{sp}, the next corollary states the comparison between the screening effort in the private economy with fintech lending only, in the economy with data selling, and in the social planner problem.

Corollary 2. *$\theta_{sp}<\theta^*$, so that the fintech lender in the economy without fintech-bank collaboration over-invests in the screening technology. There exists a B_2 such that $\theta_{DS}<\theta^*$ if $b>B_2$ and $\theta_{DS}\geq\theta^*$ otherwise.*

@enc

[16]For example, viewed as a regulator, the social planner may ban the use of certain customer data from being used for loan screening, or restrict the kinds of technologies that may be used. We also assume the social planner cannot direct financing resources from the bank to the fintech lender frictionlessly.

Figure 3: Bank Funding Advantage and Screening Effort



The screening-effort comparison is also plotted in Figure 3. First, we discuss the case with no fintech-bank collaborations. The overinvestment in the fintech screening technology can be attributed to the asymmetric information between borrowers and lenders. Generally, good-type borrowers have a higher likelihood of passing the fintech screening compared to bad-type borrowers. As a result, good-type borrowers prefer contracts with lower interest rates and are more tolerant of rigorous screening. In our model, a good-type borrower can always pass the screening and therefore prefers any lending contract that offers the lowest borrowing rate. Consequently, a bad-type borrower with a project that has a negative net present value must mimic the preferences of a good-type borrower in the lending market. This leads to the fintech lender's objective of minimizing the interest rate offered to the market. Compared to the social planner problem, the fintech lender does not consider the impact of their screening on the expected value of bad-type borrowers. As a result, the fintech lender in the private economy invests excessively in screening technology.

Therefore, our model suggests limiting fintech lenders' investment in screening technology can improve overall welfare. However, directly regulating these investments may prove challenging as they are observable or measurable. According to our model, encouraging collaborations between fintech lenders and banks can be an alternative way to alleviate the overinvestment in fintech screening technology. Allowing fintech lenders to collaborate with banks or other lower-funding-cost lenders increases the opportunity cost of screening, as the fintech lender now needs to contribute their high-funding-cost capital to demonstrate a commitment to proper screening efforts. Consequently, allowing fintech-bank collaborations can effectively mitigate the issue of overinvestment in fintech screening technologies.

However, it is important to note that fintech-bank collaborations may decrease the fintech lender's screening incentive so much that the private economy underinvests in screening technology. Underinvestment is more likely to occur when the bank's relative funding-cost advantage is large (Figure 3). In that case, fintech-bank collaborations rely too little on fintech funding, causing a lack of skin-in-the-game and potential underinvestment in fintech screening.

It is worth noting that when banks have large funding-cost advantage over fintech lender, the optimal data selling contract tends to generate higher screening efforts compared to the optimal joint lending contract (Figure 2), alleviating concerns about underinvestment in screening. In this regard, innovations which make credit history data contractable can improve social welfare not only by reducing borrowing rates in the economy but also bringing fintech investment closer to the socially optimal level, especially when the traditional banking sector possesses a substantial funding-cost advantage.

4 Discussions

4.1 Selling Loans versus Data

In Section 3.2, we studied the optimal fintech-bank collaboration contract when only $t_1 - t_0$, the time interval between the date when the borrower applied for a loan and the current date, is contractable into the collaboration contract. However, the borrower's credit history data $\Phi_t = (t - t_0, i_s, i_{d,t})$ also includes information about the borrower's screening result i_s and default history $i_{d,t}$. Now, we analyze the case where the contract can also be contingent on the borrower's screening result and default history. We define $i_t = (1-i_s)i_{d,t}$ to be the binary variable that indicates whether the borrower has good credit history ($i_t = 0$) or bad credit history ($i_t = 1$).

A fintech-bank collaboration contract now specifies $\{\alpha, P, \tau, i_{t_0+\tau}\}$: like before, α captures the fintech lender's share of the loan, P is the one-time service fee paid from the bank to the fintech lender at date $t_1 = t_0 + \tau$, but now the collaboration happens and the fee is paid when the length of the borrower's credit history is τ and the borrower has not defaulted ($i_{t_0+\tau} = 0$). So, at date t_1, the bank pays the service fee P to the fintech lender if the borrower' project has not matured at date t_1 and the borrower has good credit history. The difference between this collaboration contract and that in the data selling in the previous subsection is that now the service fee payment is contingent on the borrower having good credit history.

Similar to Section 3.2, Lemma 2 still holds and $\alpha = 0$. In the optimal contract, the fintech lender lends to the borrower for τ units of time and sells the borrower's credit history data to the bank for subsequent lending only if the borrower has a good credit history. At date $t_0 + \tau$, when the fintech lender executes the collaboration contract, conditional on the borrower's project not yet maturing, a borrower with good credit history has an ongoing fintech loan. So the optimal collaboration contract can be implemented by the fintech lender selling the entire loan to the bank at date $t_0 + \tau$. We call this type of collaboration contract a *loan selling* contract.

Now we solve for the optimal loan selling contract. At date t_0, the fintech lender chooses (R, θ) to minimize the lending rate, taking the collaboration contract as given. $R = R(\tau, P)$ and $\theta = \theta(\tau, P)$ solves

$$c'(\theta) = (1-e^{-(\rho+\lambda+\eta)\tau})(1-\pi)[1-\frac{R+\lambda}{\rho+\lambda+\eta}] \tag{11}$$

$$c(\theta)+c'(\theta)(1-\theta) = e^{-(\rho+\lambda)\tau}(\pi+e^{-\eta\tau}(1-\pi)(1-\theta))P+(1-e^{-(\rho+\lambda)\tau})\pi(\tfrac{R+\lambda}{\rho+\lambda}-1)+ (1-e^{-(\rho+\lambda+\eta)\tau})(1-\pi)(1-\theta)(\tfrac{R+\lambda}{\rho+\lambda+\eta}-1). \tag{12}$$

The optimal collaborating contract (τ^*, P^*) solves

$$\min_{\tau \geq 0, P \geq 0} R(\tau, P) \quad \text{subject to}$$

$$(\pi + e^{-\eta\tau}(1-\pi)(1-\theta))P \leq \pi(\frac{R(\tau,P)+\lambda+b}{\rho+\lambda} - 1) + e^{-\eta\tau}(1-\pi)(1-\theta(\tau,P))(\frac{R(\tau,P)+\lambda+b}{\rho+\lambda+\eta} - 1).$$

Denote the time length of fintech lending in the optimal loan selling contract by τ_{LS} and the corresponding screening effort and interest rate by (θ_{LS}, R_{LS}). Corollary 3 compares the optimal loan selling contract with the optimal data selling contract in Section 3.2.

Corollary 3. $R_{DS} < R_{LS}$, so that the fintech lender prefers selling borrowers' credit history data rather than selling loans to banks.

Under a *data selling* contract, the fintech lender can receive the service fee from the bank as long as the borrower's project has not matured when the collaboration is executed. In contrast, under a *loan selling* contract, the fintech lender receives the service fee only if the borrower's project has not matured and the borrower has good credit history. The fact that the service fee is contingent on the borrower having good credit history gives the fintech lender an additional disincentive to screen, because the probability of receiving the service fee $(\pi + e^{-\eta\tau}(1-\pi)(1-\theta))$ at date $t_0 + \tau$ will be lower if the fintech lender exerts a higher screening effort. In other words, it is *less efficient* to incentivize fintech screening under a *loan selling* contract than under a *data selling* contract, all else equal. As a result, the optimal data selling contract outcompetes the optimal loan selling contract.

In sum, when borrowers' credit history data is contractable, fintech lenders prefer selling borrowers' credit history data over selling loans to banks. This is because selling credit history data is *more efficient* in incentivizing fintech screening, which allows fintech lenders to offer lower interest rates in the lending market.

Database Reconstruction & Reverse-Engineering Concerns

Compared to selling loans (which is equivalent to selling credit history data of borrowers with good credit history), selling credit history data of all relevant borrowers would require the fintech lender to transfer more information to the bank. This difference leads to a potential concern that the bank may use credit history data of all relevant borrowers to reverse-engineer the fintech lender's screening model. The extent to which a fintech lender concerns about such reverse engineering depends crucially on the source of the fintech lender's screening advantage.

If the fintech lender's screening advantage comes largely from its collection or possession of alternative data, it is very hard for the bank to distill useful information from analyzing borrowers' credit history data together with standard credit-risk-relevant data. In this case, selling credit history data would not raise much concerns about reverse engineering. However, in practice, if the fintech lender's screening advantage comes largely from applying advanced machine learning techniques on standard financial data in screening, fintech lenders should be more concerned about reverse engineering, so they may instead choose to use loan selling or even joint lending contracts, even when data selling contracts are more efficient in inducing fintech screening and reducing lending risks.

4.2 Data Exclusivity: Skin-in-the-Game vs. Tokenization

It is worth noting that our analysis implicitly assumes that the fintech lender can exclusively transfer the borrower's credit history data to one bank. However, the data cannot be sold exclusively to one entity if there is no mechanism to transfer data ownership without permitting the duplication and resale of the data for other uses. This property of data is known as non-rivalrousness (Jones and Tonetti 2020).

In our setting, a bank may not be willing to purchase the borrower's credit history data knowing that other banks may do so, because competition in the lending market would reduce the information edge of the credit history data. Thus, the viability of the data selling contract depends crucially on whether the economy has a mechanism to facilitate exclusive data selling.

Exclusive data selling can be implemented in at least two ways. One way to ensure the exclusive data selling is to have the fintech lender facilitate and manage the bank loan associated with the sale of credit history data. The participation of the fintech lender in the lending can assure the bank that the sale of credit history data is exclusive. For instance, the optimal data selling contract can require the fintech lender to receive the service fee after she successfully helps facilitate the bank loans to those borrowers with good credit histories. This is an indirect incentive-based method to ensure data exclusivity.

Another way to ensure exclusive sales of credit history data, even in settings with many sellers and buyers, is possible due to recent developments in financial technology due to tokenization, a method that combines cryptography with tradability on a ledger. Data tokenization is a process in which sensitive data is replaced with a unique identifier called a token which is mapped back to the original data through the tokenization system. The tokenization allows security, anonimity, and most importantly, access control and auditability. For example, a token may be constructed with a smart contract which ensures that not only is the initial data encrypted, no copies of the data can be made, and access and ownership of that data "token" can also be tied to a private key which can be transferred. The tokenization system can also be externally audited by a trusted party to ensure the fintech lender has not made copies of the data. Once transferred, the originating party can no longer view the data.[17] This token acts as a reference to the original data but does not contain any actual sensitive information. By tokenizing data, firms are able to exclusively transfer it to another entity while maintaining its security and privacy. This allows for the secure exchange of data without exposing the actual sensitive information to unauthorized parties. This is a direct contract-based method to ensure data exclusivity.

[17] Data tokens in the cryptocurrency ecosystem frequently contain such a feature. One example of such a system is Ocean Protocol, which tokenizes data to transfer ownership and access in a privacy-protected manner. In this case, a credit scoring system at a bank need only take in "blinded" tokens for analytics without any human directly viewing the data.

5 Conclusion

In this paper, we present a model of the fintech-bank lending ecosystem that allows fintech lenders and banks to compete and collaborate in various ways. In the model, encouraging fintech-bank collaborations can improve financial inclusion and reduce excessive investment in screening technology. We study how different collaboration models affect the cost of borrowing, fintech screening, and social welfare. Comparing different collaboration models, we find data selling provides a more effective way to incentivize fintech investments in screening technology. Under data-selling contracts, fintech lenders serve as an on-ramp to the financial system by selling borrowers' credit history data to banks, who take over subsequent lending. However, depending on the funding-cost difference between fintech lenders and banks, privately-optimal data selling can induce too much or too little investment in screening technologies. Therefore, we do not expect to see a one-size-fits-all financial regulation on the lending ecosystem but expect to find different types of economies reacting differently. For instance, our model suggests that countries where banks have significant funding-cost advantages over fintech lenders tend to restrict data-selling to improve social welfare. In contrast, countries with little funding-cost differences between fintech lenders and banks tend to advocate data-selling.

References

Bennardo, A., Pagano, M., and Piccolo, S. (2015). Multiple bank lending, creditor rights, and information sharing. *Review of Finance*, 19(2):519–570.

Berg, T., Burg, V., Gombović, A., and Puri, M. (2020). On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *The Review of Financial Studies*, 33(7):2845–2897.

Berger, A. N. and Black, L. K. (2011). Bank size, lending technologies, and small business finance. *Journal of Banking and Finance*, 35(3):724–735.

Berger, A. N., Cerqueiro, G., and Penas, M. F. (2015). Market Size Structure and Small Business Lending: Are Crisis Times Different from Normal Times? *Review of Finance*, 19(5):1965–1995.

Borgogno, O. and Colangelo, G. (2020). The data sharing paradox: BigTechs in finance. *European Competition Journal*, 16(2-3):492–511.

Carbo-valverde, S., Degryse, H., and Rodríguez-fernández, F. (2015). The impact of securitization on credit rationing : Empirical evidence. *Journal of Financial Stability*, 20:36–50.

Carter, D. A. and McNulty, J. E. (2005). Deregulation, technological change, and the business-lending performance of large and small banks. *Journal of Banking and Finance*, 29(5):1113–1130.

Chatterjee, S., Corbae, D., Dempsey, K., and Rios-Rull, J.-V. (2020). A Quantitative Theory of the Credit Score. *SSRN Electronic Journal*.

Cole, R. and Sokolyk, T. (2016). Who needs credit and who gets credit? Evidence from the surveys of small business finances. *Journal of Financial Stability*, 24(March 2014):40–60.

Council, F. B. (2021). How fintech lending trends benefit small businesses. *Forbes*. Accessed on 2023-10-29.

DeYoung, R., Frame, W. S., Glennon, D., and Nigro, P. (2011). The Information Revolution and Small Business Lending: The Missing Evidence. *Journal of Financial Services Research*, 39(1-2):19–33.

Djeundje, V. B., Crook, J., Calabrese, R., and Hamid, M. (2021). Enhancing credit scoring with alternative data. *Expert Systems with Applications*, 163:113766.

Duarte, J., Siegel, S., and Young, L. (2012). Trust and credit: The role of appearance in peer-to-peer lending. *Review of Financial Studies*, 25(8):2455–2483.

Farboodi, M., Mihet, R., Philippon, T., and Veldkamp, L. (2019). Big Data and Firm Dynamics. *AEA Papers and Proceedings*, 109:38–42.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., and Walther, A. (2021). Predictably unequal? the effects of machine learning on credit markets. *Journal of Finance*.

Fuster, A., Plosser, M., Schnabl, P., and Vickery, J. (2019). The Role of Technology in Mortgage Lending. *Review of Financial Studies*, 32(5):1854–1899.

Gao, Q., Lin, M., and Sias, R. W. (2018). Words matter: The role of texts in online credit markets. *Working Paper*.

Hau, H., Huang, Y., Shan, H., and Sheng, Z. (2018). Fintech credit, financial inclusion and entrepreneurial growth. *Working Paper*.

He, Z., Huang, J., and Zhou, J. (2023). Open banking: Credit market competition when borrowers own the data. *Journal of financial economics*, 147(2):449–474.

He, Z., Jiang, S., Xu, D., and Yin, X. (2021). Investing in lending technology: It spending in banking. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2021-116).

Jagtiani, J. and Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, 100(March):43–54.

Jones, C. I. and Tonetti, C. (2020). Nonrivalry and the Economics of Data. *American economic review*, 110(9):2819–2858.

Mills, K. (2016). The State of Small Business Lending: Innovation and Technology and the Implications for Regulation. *SSRN Electronic Journal*.

Mitchell, K. and Pearce, D. K. (2011). Lending technologies, lending specialization, and minority access to small-business loans. *Small Business Economics*, 37(3):277–304.

Morse, A. (2015). Peer-to-Peer Crowdfunding: Information and the Potential for Disruption in Consumer Lending. *Annual Review of Financial Economics*, 7:463–482.

Netzer, O., Lemaire, A., and Herzenstein, M. (2019). When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications. *Journal of Marketing Research*, 56(6):960–980.

Pagano, M. and Jappeli, T. (1993). Information Sharing in Credit Markets. *The Journal of Finance*, 48(5):1693–1718.

Parlour, C. A., Rajan, U., and Zhu, H. (2022). When fintech competes for payment flows. *The Review of Financial Studies*, 35(11):4985–5024.

Schweitzer, M. and Barkley, B. (2017). Is fintech good for small business borrowers? impacts on firm growth and customer satisfaction. *Working Paper*.

Sedunov, J. (2017). Does Bank Technology Affect Small Business Lending Decisions? *Journal of Financial Research*, 40(1):5–32.

Semenova, M. (2008). Information sharing in credit markets: Incentives for incorrect information reporting. *Comparative Economic Studies*, 50(3):381–415.

Stulz, R. M. (2019). FinTech, BigTech, and the Future of Banks. *Journal of Applied Corporate Finance*, 31(4):86–97.

Vives, X. (2017). The impact of fintech on banking. *European Economy*, (2):97–105.