When FinTech Competes for Payment Flows*

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Abstract

We study the impact of FinTech competition in payment services when a bank uses payment data to learn about consumers' credit quality. Competition from FinTech payment providers disrupts this information spillover. The bank's price for payment services and its loan offers are affected. FinTech competition promotes financial inclusion, may hurt consumers with a strong bank preference, and has an ambiguous effect on the loan market. Both FinTech data sales and consumer data portability increase bank lending, but the effects on consumer welfare are ambiguous. Under mild conditions, consumer welfare is higher under data sales than with data portability.

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Abstract

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1 Introduction

Historically, banks have offered a bundle of services, including payment processing and loans to both businesses and individuals. Currently, in the United States, technology giants such as Apple and more specialized companies such as Paypal and Venmo also compete in payments. In China, mobile payments made through processors such as Alipay and WeChat Pay account for over 16% of GDP (see Bank for International Settlements (2019)). In Kenya, M-Pesa is used by about three-quarters of households (see Jack and Suri (2014)). FinTech competition in payments has been supported by regulations such as the Payment Services Directive 2 in Europe (which requires banks to provide customers' account information to third-party payment providers in a standardized format) and the Open Banking initiative in the UK and Canada.

The rise of competition for standalone payments uniquely disrupts the historical banking model because payment flows are informative about credit risk. For example, Black (1975) observes that the flows in an account allow a bank to better understand a customer's credit quality. An extensive empirical literature on consumer and business credit confirms this intuition.[1]

In this paper, we construct a parsimonious model of a bank as a payment processor and lender, and consider the effect of low-cost competition in payments. We focus on payments for two reasons. First, payment service is economically large and important. Second, competition in payments is relatively new: prior to the rise of digital payments the only

[1] McKinsey (2019) states that "payments generate roughly 90 percent of banks' useful customer data." The connection between transaction account flows and credit quality has been made by Puri, Rocholl, and Steffen (2017) using German data on consumers, Mester, Nakamura, and Renault (2007) using Canadian data on small businesses, and Hau, Huang, Shan, and Sheng (2019) using data on loans made by Ant Financial to online vendors. Agarwal, Chomsisengphet, Liu, Song, and Souleles (2018) show that relationship customers in the U.S. are less likely to default on credit card debt. Liberti, Sturgess, and Sutherland (2020) find that lenders who join a commercial credit bureau early (and hence have access to the longer payment histories of borrowers), gain market share relative to lenders who join late. Rajan, Seru, and Vig (2015) find that a loss of in the loan-making process can lead to a consistent mis-estimation of default probabilities on the loan portfolio.

competition to bank-based payments was physical cash. By contrast, banks have always faced competition in the loan market.[2]

In our model, the bank is a monopolist in lending, but competes with two identical FinTech firms for payment processing. The bank and the FinTech firms have the same payment technology. The FinTech firms engage in Bertrand competition and offer payment services at a price normalized to zero. The bank strategically prices payment services to maximize its total profit, and internalizes the benefit of access to payment data. Consumers differ in their creditworthiness, which can be high or low. In addition, consumers have a value for unmodeled bank services that we label "bank affinity." Bank affinity serves to generate horizontal differentiation between the bank and the FinTech firms. A negative bank affinity means a cost to access banks. We allow the distribution of bank affinity to depend on consumers' creditworthiness.

Crucial to the model, payment processing is valuable to the provider—a payment processor can extract a signal about the credit quality of its customers from information about their transactions. Thus, a bank that does not handle the payments of a loan applicant has less precise information about their credit quality. As a result, payments have a spillover onto the credit market. This spillover has different welfare implications for consumers, banks, and regulators.

Consumers know their own credit type and, as is standard in a screening model, the bank offers a menu of two contracts to each consumer and allows them to choose. The contracts differ both in loan quantity and interest rate. The optimal screening menu has the feature that the participation constraint of the less creditworthy consumer and the incentive compatibility constraint of the more creditworthy consumer bind. Thus, the former obtains

[2] We call incumbents in the payment space "banks;" in practice, this includes large banks such as JP Morgan and Citibank, as well as card networks such as Visa and Mastercard. We call the entrants into the payment space "FinTech;" entrants comprise a diverse set of businesses from startups to small online banks to "Big Tech" firms such as Alibaba, Tencent, Amazon, and Apple.

zero surplus while the latter obtains an informational rent. The optimal menu also generates a social inefficiency — the bank distorts the loan quantity that it offers to low creditworthy consumers downward, whereas high creditworthy consumers are offered an efficient loan quantity.

A consumer's demand for bank payment services depends on their bank affinity, the price of the bank's payment service relative to non-bank options, and their expected utility from a loan. A change in the price of payment services by the bank has the expected direct effect on the bank's profit. It also has an indirect effect, as it changes the bank's set of payment customers. This in turn changes the bank's information and thus its optimal screening contracts in the loan market, which then alters consumers' expected loan market surplus and hence feeds back into the demand for bank payments.

Although standard intuition about competition may lead one to expect that FinTech competition leads to a fall in the bank's price for payment services, we present conditions under which the price instead increases. Facing FinTech entry, the bank's choice is between a higher profit margin on a narrower set of consumers versus a smaller profit margin on a broader set of consumers. The bank may choose either response, depending on the bank affinity distribution of consumers. The industrial organization literature has shown that increased competition may lead to higher prices.[3] Our model includes an addtional effect, in the novel feedback loop between consumers' demand for bank services and their expected surplus in the loan market.

The consequences of FinTech competition for loan market surpluses are intricate. As mentioned earlier, the bank's optimal menu of contracts depends on the information it has

[3]Theoretically, Chen and Riordan (2008) show that when consumer valuations have a decreasing hazard rate, the price of a good is higher under duopoly than monopoly. In a model with random consumer utilities, Gabaix et al. (2016) show that firms' markups increase in the number of firms if the distribution of consumer valuations has "fat tails." Empirically, Sun (2019) shows that in response to the entry of low-cost Vanguard index funds, funds sold with broker recommendations (i.e., likely with captive customers) increased their fees.

about each loan applicant. In choosing a payment service, all else equal, a high credit type consumer prefers mixing with a large number of low credit type consumers, which allows the high credit type to capture a greater informational rent. Faced with such a pool, the bank designs the contracts primarily to make a profit from low credit type consumers. In contrast, a bank facing a high concentration of high credit type consumers will design the contract to primarily extract surplus from such consumers. Because the bank affinities of high and low credit consumers have flexible distributions, FinTech entry may leave the bank with a consumer pool tilted toward either credit type. Therefore, the high credit consumers' loan surplus can go up or down with FinTech competition in payment. For a similar reason, high credit consumers' loan surplus is generally non-monotone in the quality of the bank's signal extracted from payment data.

Despite the subtle and nuanced changes in loan market surplus, the impact of FinTech competition is unambiguous for some consumers. In particular, those who were previously unbanked now use a FinTech firm to process payments, and benefit from financial inclusion. In contrast, consumers with strong bank affinity stay with the bank, unswayed by FinTech competition. Among such consumers, the welfare of low credit types depends purely on the price of payment services, which changes on FinTech entry. Our results therefore point to cross-sectional trade-offs across different consumer segments.

Our baseline model assumes that once payment data are diverted from the bank, they are inaccessible in the credit market. In reality, payment data are frequently used as an input for lending through FinTech-bank partnerships. For example, in 2012, a large bank in Kenya and the operator of M-Pesa mobile money formed a partnership to launch M-Shwari, which provides credit to borrowers, even if they have no banking or credit history. Bharadwaj, Jack, and Suri (2019) find that such mobile money-enabled credit quickly gained market share and increased household resilience. Using the Indian demonetization event, Ghosh, Vallee, and Zeng (2021) find that firms adopting cashless payment receive better outcomes in the credit market, consistent with their model in which cashless payment is verifiable information but cash payment is not.[4] The synergy between data and lending is also evident between Ant Group and its partner banks,[5] between Atom Bank and Plaid, and between TAB Bank and Mulesoft's Anypoint Platform, among others. Such economic relationships allow the FinTech company to transfer data to the lender.

Another possibility for data transfer is that consumers own their data and port them when needed. Policymakers and practitioners have embraced this idea. For example, GDPR (General Data Protection Regulation) in Europe suggests that consumers should have more direct control of their data. In July 2021, the Biden administration in the U.S. issued an executive order to, among other things, allow consumer portability of their data.[6] Industry initiatives such as the Financial Data Exchange seek to standardize bank payment data to allow consumers to port their data.[7]

Motivated by these developments, we compare two methods by which payment data find their way back to the lending market: FinTech firms selling data to the bank and consumers owning their data and choosing whether to port their data to the bank. In both regimes, the bank, as the sole lender, has access to the signal about a consumer's credit quality extracted from payments, even if the consumer uses a FinTech firm to process payments. The difference is that in the case of FinTech data sales, competitive FinTech firms reimburse the proceeds of data sales back to consumers in the form of subsidized payment services. In contrast, when consumers port their own data, we show that a form of unraveling effectively

[4]The lender in their model is competitive and only makes loans, whereas the bank in our model strategically prices payments and loans in two business lines.

[5]In the company's prospectus ahead of its planned IPO in Hong Kong (which was later called off by Chinese regulators), it says "[a]s of June 30, 2020, approximately 98% of credit balance originated through our platform was underwritten by our partner financial institutions or securitized." In September 2021, the Chinese government proposed a plan to split up the payment and lending arms of Alipay, and to have data be turned over to a joint venture that will be partly state-owned. See https://www.reuters.com/world/china/china-break-up-ants-alipay-force-creation-separate-loans-app-ft-2021-09-12/.

[6]See, for example https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/09/fact-sheet-executive-order-on-promoting-competition-in-the-american-economy/

[7]https://financialdataexchange.org/

forces everyone to share data with the bank for free. Put differently, while data porting is in principle voluntary, the fact that others share data imposes a negative *data externality* on those who do not. Thus, policies that aim to give consumers more direct, and potentially stricter, control of their data may have the unintended, opposite effect. In anticipation of such forced data sharing, the bank's price for payment services worsens in the regime with consumer data porting.

A third way for payment data to be used in lending is to have the FinTech firm lend directly. We exclude this possibility from our paper, in part because oligopolistic competition in screening contracts is significantly more complicated than monopolist screening. FinTech lending (or non-bank lending more broadly) has been examined extensively in the literature. For example, He, Huang, and Zhou (2021) provide a model of FinTech and bank competition in lending with consumer data sharing. Their main result is that under some circumstances open banking can make all consumers worse off, with the intuition again being partly based on unraveling. In contrast, our focus is FinTech competition in the payment market, and its effect for lending is primarily through the endogenous self-selection of consumers and the screening by the bank. These two approaches are, thus, complementary.

In recent work, Vives and Ye (2021) consider the effect of technological advances on the lending market in the presence of competing banks. In particular, technological improvement can lead to reduced welfare if it mitigates the effect of distance on screening or monitoring costs. Vives (2019) provides a detailed survey of digital disruption in banking, and Morse (2015) reviews the P2P literature up to 2015.[8]

To summarize, our analysis highlights two fundamental tensions when FinTech competes for payment flows. The first tension is between financial inclusion and disruption. For

[8]Recent empirical papers on P2P lending, crowdfunding, and online lenders include Iyer, Khwaja, Luttmer, and Shue (2016), Hildebrand, Puri, and Rocholl (2017), Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2018), Vallée and Zeng (2019), Tang (2019), and de Roure, Pelizzon, and Thakor (2019), among others.

unbanked or underbanked consumers, not only does FinTech competition provide access to more convenient electronic payment systems, but the data generated in the payment process become "hard information" that leads to increased credit provision to this population. In contrast, enhanced competition and data sharing could harm consumers who are well off in the current system. If, for example, banks respond to FinTech competition by raising their price for payment services, those who stay with the bank may be worse off. Likewise, high credit consumers may receive a lower surplus in the loan market if data sharing leads to more accurate price discrimination by banks. The trade-off between these two effects is likely country-specific. It is perhaps unsurprising that FinTech payment competition tends to be viewed as "inclusive" in developing economies and "disruptive" in developed ones.

The second tension is between a bank regulator (such as the Federal Reserve Board) and a competition regulator (such as the Federal Trade Commission). The bank regulator cares about the stability of banks, and one way to achieve its goal is to keep banks profitable. The competition regulator cares about consumer welfare. The conflict here is unavoidable. In our model, the bank receives all surplus from lending to low credit consumers, and under some conditions, data generated in the payment process harms high credit consumers. Consumer data ownership is supposed to give consumers an upper hand, but we show that this policy may backfire. How to establish consumer sovereignty over their own data while preventing a data externality and unraveling is, to the best of our knowledge, an open problem.

2 Model

Consider an economy with two financial services: electronic payment services and consumer loans.[9] There is one strategic bank that offers both loans and payment services, while two

[9] One can also interpret the model as the bank offering a different non-payment (but credit-informative) service such as investment management along with loans.

identical and competitive FinTech firms are stand-alone payment processors.[10] All are risk-neutral. For simplicity, the risk-free interest rate is normalized to be zero.

There is a unit mass of risk-neutral consumers, who may be thought of as small firms or as households. With probability ψ, each consumer is hit with a liquidity shock and requires a loan. A consumer has either a high or low repayment probability on the loan. This probability is denoted as θ_j with $j \in \{h, \ell\}$, and we refer to it as the credit type of the consumer. A mass m_h of consumers have repayment probability θ_h, while a mass $m_\ell = 1 - m_h$ have repayment probability $\theta_\ell < \theta_h$. We emphasize that the credit types θ and masses m are conditional on all available information other than payment data.[11]

Each consumer receives utility $v > 0$ from access to an electronic payment service. We assume that the quality of the payment service provided by the bank and the FinTech firms is the same.

Each consumer i with credit type θ_j also enjoys incremental utility b_i from using the bank's payment service. This idiosyncratic utility generates horizontal differentiation, and we call it *bank affinity*. The bank affinity b_i has a probability distribution conditional on credit type θ, denoted by $F(\cdot \mid \theta)$ with density $f(\cdot \mid \theta)$. Conditional on credit type θ, bank affinity is i.i.d. and has support over the entire real line. A negative bank affinity implies a cost to using the bank's payment services.

A consumer who uses neither the bank nor a FinTech firm for electronic payment services conducts all transactions in cash, in which case she receives a normalized utility of zero from payment processing. In summary, consumer i's utility from payments routed through a bank,

[10] The large literature on relationship banking suggests that banks are able to exercise some market power in lending to long-term consumers (see, e.g., Petersen and Rajan (1995)). On the deposit side, Drechsler, Savov, and Schnabl (2017) show that bank behavior following changes in the Federal funds rate is consistent with banks having market power in deposits. More broadly, competition can be represented on a continuum, with the idea that FinTech firms are more competitive than banks. For modeling simplicity, we consider the bank to be a monopolist and FinTech firms to be perfectly competitive.

[11] For households and individuals, other observable information includes (but is not limited to) income, wealth, and credit score. For businesses, other observable information includes revenues and profits.

a FinTech firm, or from using cash are, respectively, $v + b_i$, v and 0.

The sequence of events is depicted in Figure 1.

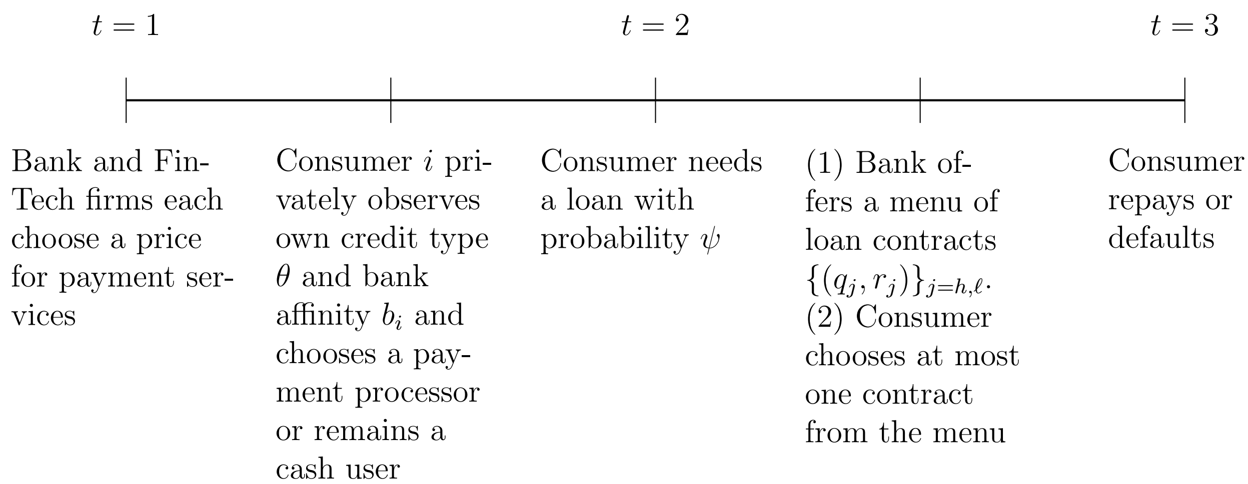


Figure 1: **Timing of Events**

At date $t = 1$, consumer j privately observes her bank affinity b_j and her own credit type θ_j. She then chooses a payment processor or remains a cash user. The FinTech firms, acting as Bertrand competitors, charge zero for payment processing (a normalization), whereas the bank chooses a price p. In practice, the price p consists of account fees and below-market deposit interest rate, among others. The timing reflects the fact that payments are ongoing and choosing a payment processor is typically a long-term decision.

At $t = 2$, with probability $\psi > 0$ each consumer receives a liquidity shock and applies for a loan at the bank. The bank engages in monopolistic screening, and offers a menu of contracts, $\{(q_j, r_j)\}_{j=h,\ell}$, with the contract (q_h, r_h) targeted to the high credit type and the contract (q_ℓ, r_ℓ) targeted to the low credit type. The consumer chooses at most one item from the menu.

At date $t = 3$, if the consumer receives a loan, she either repays the loan fully by paying $q(1 + r)$ to the bank, or defaults. For simplicity, in the latter case, we assume that the bank recovers nothing from the consumer.

Key variables of the model, including those introduced here and in subsequent sections, are tabulated in Appendix A for ease of reference. All proofs are in Appendix B.

3 Loan Market

We begin by analyzing the loan market at time 2. Payoffs from this market will affect both banks and customers in the payments processing market. Suppose a consumer of credit type θ accepts a loan contract (q, r). Their utility from the loan is:

$$w(q, r \mid \theta) \;=\; \theta\{Aq - q(1+r)\} - \frac{\lambda}{2}(1-\theta)q^2, \tag{1}$$

where $A > 1$ and $\lambda > 0$. Here, Aq is the utility earned from the project the funds are used for. We assume that this utility is earned only if the consumer repays the loan. The amount repaid is $q(1+r)$. If the consumer defaults, which happens with probability $1-\theta$, they incur a reputation penalty captured by the term $\frac{\lambda}{2}q^2$. This term ensures that defaulting is costly, and is more costly for low credit type consumers.[12]

The profit of the bank from a loan (q, r) to a consumer with credit type θ is

$$\pi(q, r \mid \theta) \;=\; \theta q(1+r) - q - \frac{\gamma}{2}q^2. \tag{2}$$

The first term on the right-hand side is the expected repayment. The second term represents the opportunity cost of the loan. The last term represents a capital charge against the loan. Here, $\gamma > 0$, so the capital charge is convex in the size of the loan and independent of the type of the borrower.

The first-best outcome maximizes the total surplus between the bank and the consumer,

[12] Technically, the quadratic default penalty ensures that the single-crossing property is satisfied. The slope of an indifference curve of credit type θ_j is $-\frac{\partial w/\partial q}{\partial w/\partial r} = \frac{1}{q}\{A - r - (\frac{1}{\theta_j} - 1)\lambda q\}$. As θ_j increases, $-\frac{1}{\theta_j}$ increases, so if $\lambda > 0$ the single-crossing property is satisfied.

that is, the sum of equations (1) and (2). The total surplus for a given θ is

$$(\theta A - 1)q - \left(\frac{\lambda}{2}(1-\theta) + \frac{\gamma}{2}\right)q^2.$$

The first-order condition is $(\theta A - 1) - \{\gamma + \lambda(1-\theta)\}q = 0$, and it is immediate to see that the second-order condition is satisfied.

Hence, the first-best quantity for credit type θ_j is

$$q_j^f = \frac{\theta_j A - 1}{\gamma + \lambda(1-\theta_j)}. \tag{3}$$

An increase in θ_j increases the loan quantity q^f. That is, in the first-best outcome, higher credit types receive larger loans.

The bank in the model has noisy information about a loan applicant, and acts as a monopolistic screener. We solve for its optimal loan contract offers using standard mechanism design techniques. Appealing to the revelation principle, in order to screen consumers, the bank offers two possible contracts, one targeted to each credit type. Crucial to its choice of menu is its belief about the credit type of the consumer when she applies for a loan at the bank.

The bank's prior at the start of the game is that a consumer has high credit type with probability m_h. This prior probability is updated in two ways. First, as we show in Section 4 below, the relative mix of high and low credit types who either use the bank for payment services or use an alternate payment processing method can differ from the masses m_h and m_ℓ. Therefore, knowing whether a consumer is a bank payment customer or not allows the bank to update its beliefs. Second, as elaborated below, for its own payment customers, the bank can extract an additional signal about credit type. Given its information about a particular customer, let μ_h denote the posterior probability the bank places on a loan applicant being the high credit type, with $\mu_\ell = 1 - \mu_h$ the probability the applicant is the low credit type.

The optimal menu of loan contracts maximizes the bank's expected profit subject to incentive compatibility and individual rationality constraints on the consumer. The bank's problem is:

$$\max_{q_h, r_h, q_\ell, r_\ell} \sum_{j=h,\ell} \mu_j [\theta_j q_j (1 + r_j) - q_j - \tfrac{\gamma}{2} q_j^2] \tag{4}$$

$$\text{subject to :} \quad (IC_h) \quad w_h(q_h, r_h) \geq w_h(q_\ell, r_\ell), \tag{5}$$

$$(IC_\ell) \quad w_\ell(q_\ell, r_\ell) \geq w_\ell(q_h, r_h), \tag{6}$$

$$(IR_h) \quad w_h(q_h, r_h) \geq 0, \tag{7}$$

$$(IR_\ell) \quad w_\ell(q_\ell, r_\ell) \geq 0. \tag{8}$$

Here, inequalities (5) and (6) are the incentive compatibility conditions for types θ_h and θ_ℓ, and inequalities (7) and (8) are the individual rationality constraints. We assume that the reservation utility of each credit type is zero.

We first show that the loan contracts the bank offers depend on its posterior beliefs only through the likelihood ratio that the consumer is a high versus a low credit type. Let $\kappa = \frac{\mu_h}{\mu_\ell}$ denote this likelihood ratio when the consumer applies for a loan.

Proposition 1. *A bank with a posterior likelihood ratio κ optimally offers two loan contracts, (q_j, r_j) for $j = h, \ell$, with*

(i) $q_\ell = \frac{\theta_\ell A - 1}{\gamma + \lambda(1-\theta_\ell) + \lambda\kappa\left(\frac{\theta_h}{\theta_\ell} - 1\right)} < q_\ell^f$, *and r_ℓ is chosen to satisfy $w_\ell(q_\ell, r_\ell) = 0$.*

(ii) $q_h = q_h^f = \frac{\theta_h A - 1}{\gamma + \lambda(1-\theta_h)}$, *and r_h is chosen to satisfy $w_h(q_h, r_h) = w_h(q_\ell, r_\ell) > 0$.*

Consumers with credit type θ_h accept the contract (q_h, r_h), and consumers with credit type θ_ℓ accept the contract (q_ℓ, r_ℓ).

The optimal menu therefore induces complete separation, with the high and low credit types accepting different loan contracts. The quantity offered to the low credit type is distorted downward from the first-best quantity. The low credit type receives zero surplus in the loan market, and the binding IR constraint determines their interest rate. In contrast, the high credit type receives the first best quantity, q_h^f, and earns a positive surplus.

As is clear from Proposition 1 part (i), the degree to which the quantity for the low credit type is distorted downwards depends on the bank's beliefs about the customer, as captured by the likelihood ratio the customer is the high versus the low credit type. The higher the chance a customer is the high credit type, the more profitable it is to ensure that their IC constraint binds, and so the bigger the distortion in the quantity offered to the low types.

We now describe how the bank updates its beliefs over credit types of loan applicants. The initial likelihood ratio of an applicant being the high versus the low credit type is $\frac{m_h}{m_\ell}$. After observing whether the applicant is a bank payment customer or not, the likelihood ratio is updated to an intermediate ratio ρ, which differs across bank payment customers and non-customers. In addition, in the base model, on its own payment customers the bank can access and extract information from the payment data about the applicant, which allows it to update the intermediate likelihood ratio ρ on its own customers.[13]

The payment data of a consumer yield the bank a signal $s \in \{s_\ell, s_h\}$ of the consumer's credit type. For some $\alpha \geq 1$,

$$P(s = s_h \mid \theta_h) = P(s = s_\ell \mid \theta_\ell) = \frac{\alpha}{1+\alpha}, \quad P(s = s_h \mid \theta_\ell) = P(s = s_\ell \mid \theta_h) = \frac{1}{1+\alpha}. \tag{9}$$

Thus, after observing the payment signal, the bank updates the intermediate likelihood ratio ρ to $\rho\alpha$ if the signal is s_h, and to $\frac{\rho}{\alpha}$ if the signal is s_ℓ.

Here α captures the bank's ability to extract useful information from the payment signal. If $\alpha = 1$, the additional signal from payments is pure noise, and as $\alpha \to \infty$, the signal

[13] The fact that payment data reside with the consumer's bank further justifies the assumption that the bank has market power in lending. If a consumer uses Bank 1 for payments, Bank 2 does not have access to this information unless there is data portability by the consumer.

perfectly reveals the credit type.

We say that a bank is "informed" (denoted by superscript ^{I}) if it has access to the consumer's payment history, and "uninformed" otherwise (denoted by superscript ^{U}). Proposition 2 shows the consumer surplus and bank profit from each credit type depending on the bank's information status. From Proposition 1, there is a complete separation, with low credit types accepting the contract (q_ℓ, r_ℓ) and high credit types accepting (q_h, r_h). Further, the loan quantity q and interest rate r depends on the bank's posterior likelihood ratio κ. In turn, κ depends on the intermediate likelihood ratio ρ (after the bank has observed whether the applicant is a payment customer, but before it has obtained the payment signal), the signal obtained from payments s, and the precision of the payment signal, α. For notational convenience, in Proposition 2, we write κ as a function of the signal s.

Proposition 2. *Let ρ be the intermediate likelihood ratio of the bank, before it observes the signal from the loan applicant's payment data, and $\kappa(s)$ the posterior likelihood ratio after observing payment signal s. Then:*

(i) Among bank payment customers,

(a) Low credit type consumers receive zero surplus from the loan market, that is, $w_\ell^I = 0$. The bank's expected profit from such a consumer is

$$\pi_\ell^I = E_s \left[Aq_\ell(\kappa(s)) - q_\ell(\kappa(s))(1 + r_\ell(\kappa(s))) - \frac{\lambda(1-\theta_\ell)+\gamma}{2}(q_\ell(\kappa(s)))^2 \mid \theta_\ell \right]. \quad (10)$$

(b) High credit type consumers receive an expected surplus

$$w_h^I = \left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{\lambda}{2} E_s[(q_\ell(\kappa(s)))^2 \mid \theta_h]. \quad (11)$$

The bank's expected profit from such a consumer is

$$\pi_h^I = Aq_h^f - q_h^f(1 + E_s[r_h(\kappa(s)) \mid \theta_h]) - \frac{\lambda(1-\theta_\ell)+\gamma}{2}(q_h^f)^2 - w_h^I. \tag{12}$$

(ii) Among consumers who adopt another payment option,

(a) Low credit type consumers receive zero surplus from the loan market, that is, $w_\ell^U = 0$. *The bank's expected profit from such a consumer is*

$$\pi_\ell^U = Aq_\ell(\rho) - q_\ell(\rho)(1 + r_\ell(\rho)) - \frac{\lambda(1-\theta_\ell)+\gamma}{2}(q_\ell(\rho))^2. \tag{13}$$

(b) High credit types receive an expected surplus

$$w_h^U = \Big(\frac{\theta_h}{\theta_\ell} - 1\Big)\frac{\lambda}{2}(q_\ell(\rho))^2. \tag{14}$$

The bank's expected profit from such a consumer is

$$\pi_h^U = Aq_h^f - q_h^f(1 + r_h(\rho)) - \frac{\lambda(1-\theta_h)+\gamma}{2}(q_h^f)^2 - w_h^U. \tag{15}$$

Notice that in part (a), an expectation is taken over signals given the credit type. When the credit type is θ_h, the posterior likelihood ratio κ is equal to $\rho\alpha$ with probability $\frac{\alpha}{1+\alpha}$ and $\frac{\rho}{\alpha}$ with probability $\frac{1}{1+\alpha}$, with the probabilities being reversed when the credit type is θ_ℓ.

The payoffs to the low and high credit type consumers follow immediately from the optimal contracts presented in Proposition 1. The bank's profit for each type of consumer can then be determined as the total surplus generated by the loan minus the surplus obtained by the consumer. As the low credit type consumer is held down to their reservation constraint, the bank retains all the surplus from the loan. In the case of the high credit type consumer, the bank obtains the surplus from the loan less the high credit type's information rent.

Observe that the high credit type's information rent, w_h^I or w_h^U as the case may be, is strictly decreasing in ρ, the intermediate likelihood ratio. That is, all else equal, when applying for a loan the high credit type prefers to be in a pool with a large number of low credit types, than in a pool with mostly high credit types. If a consumer were revealed to be the high credit type for sure, the monopolist bank lender would capture all the surplus from the loan contract, holding the consumer down to their reservation utility.

An immediate corollary to Proposition 2 is that on a given loan applicant, the bank earns a higher profit if it is informed, i.e., has access to the payment data.

Corollary 2.1. *For all $\alpha > 1$, when a consumer applies for a loan, the bank's profit from the loan is strictly higher if the bank is informed compared to when it is uninformed.*

4 Payment Market

Each payment service provider chooses a profit-maximizing price for its services. For simplicity, we normalize the cost of providing payment services to zero for both the bank and the FinTech firms. In the context of our model, the price charged by the bank for payment services, p, is the total economic cost of maintaining a payment account at the bank. This includes account fees and the below-market interest rate paid on deposits.

If a consumer of credit type θ_j and bank affinity b chooses the bank to process payments, their overall utility is

$$W_j^b \quad = \quad v - p + b + \psi w_j^I, \tag{16}$$

where $v > 0$ is the utility from using electronic payment services (as opposed to using cash), and w_j^I is the utility from a loan offered by the bank. All consumers face the same price p at time 1 because at time 1 the bank does not have any information on the credit type of the consumer.

The bank affinity variable b admits different interpretations, and the distribution can vary both across countries and across groups in the same country.[14] We use the affinity distribution to capture any reason a consumer may prefer a bank or an alternate payment method, including intrinsic preference or a cost of using either service. Thus, the bank affinity distribution not only depends on the credit type, but should also be viewed as country-specific.

For example, consumers who value unmodeled bank services such as wealth management (say, older and wealthier consumers) have a positive and high b. Conversely, those who have a high cost to accessing a bank (say, consumers in rural India or Kenya[15] who live far from the nearest bank branch), have a large negative b. The variable b may also reflect a relative preference between the bank and a FinTech firm, so it may be negative if the FinTech mobile app is slicker and easier to use. Conversely, if a consumer worries about fraud or data breaches with mobile payments, she would assign a high cost for using FinTech firms, and would have a positive b.

The support of F_j, the distribution of b given credit type θ_j, is unbounded to ensure that the bank's optimal price for payment services remains finite. We assume that the demand goes to zero sufficiently rapidly as the price goes to infinity.

Assumption 1. *As the price of payment services becomes large, the bank's revenue from payment services goes to zero. Specifically,* $\lim_{p\to\infty} p(1 - F_j(p)) = 0$ *for each* $j = h, \ell$.

We consider both a benchmark case in which only the bank provides payment services (with cash being the alternative) and a base case in which FinTech firms compete with the

[14] For example, Demirgüç-Kunt et al. (2018) report gender gaps among those who have bank accounts of 7% in high income countries and 9% in low income countries, and mention that "Globally, about 1.7 billion adults remain unbanked — without an account at a financial institution or through a mobile money provider."

[15] For example, on Kenya, Jack and Suri (2014) write: "In a country with 850 bank branches in total, roughly 28,000 M-PESA agents (as of April 2011) dramatically expanded access to a very basic financial service—the ability to send and receive remittances or transfers."

bank in payment services. Intuitively, in each case high affinity consumers use the bank and low affinity consumers use the alternative service. We further show that when FinTech services are available, no consumer continues to use cash. The FinTech firms compete with each other in Bertrand fashion, and charge a price of zero for payment services.

Recall that w_j^I (w_j^U) is the surplus credit type θ_j obtains from a loan when the bank is informed (uninformed).

Lemma 1. *For each credit type θ_j, where $j = h, \ell$, the threshold consumer indifferent between using the bank and an alternative payment service is given by:*

(i) $b_j^m(p) = p - v - \psi(w_j^I - w_j^U)$ when the bank is a monopoly provider of payment services.

(ii) $b_j^c(p) = p - \psi(w_j^I - w_j^U)$ when FinTech firms also provide payment services.

Consumers with bank affinity greater than the threshold use the bank for payment services, and those with affinity lower than the threshold use cash in case (i) and a FinTech firm in case (ii).

Given the type-dependent bank affinity distributions, the bank faces a downward-sloping demand curve for its payment services. Let z represent the incremental utility from bank payment services over the next best alternative (where $z = v$ if only the bank provides payment services and $z = 0$ after FinTech entry). Then, we can write the demand for the bank's payment services from consumers with credit type θ_j as $1 - F_j(p - z - \psi\Delta_j^w(p, z))$, where $\Delta_j^w(p, z) = w_j^I - w_j^U$ is the incremental surplus from a loan if the consumer uses the bank rather than alternative payment service. That is, rational consumers incorporate the value of a potential banking relationship when they make their choice. From Proposition 2, $w_\ell^I = w_\ell^U = 0$, so it follows that $\Delta_\ell^w = 0$. However, the demand from high credit type consumers for payment services depends on the endogenous incremental surplus from a loan when the bank is informed (i.e., on Δ_h^w). Economically, this means that even if the two affinity distributions are the same, so that $F_h = F_\ell$, the induced distributions of who chooses the bank for payment services differ between high and low types.

From a technical point of view, this feature implies that equilibrium entails a fixed point in consumer demand, as Δ_h^w in turn depends on the mass of each credit type that use the bank for payment services. To see this, observe that the intermediate likelihood ratio for a bank payment customer who applies for a loan is $\rho^B = \frac{m_h}{m_\ell} \times \frac{1-F_h(p-z-\psi\Delta_h^w(p,z))}{1-F_\ell(p-z)}$, recognizing that $\Delta_\ell^w = 0$. Similarly, the intermediate likelihood ratio for a non-customer of the bank is $\rho^N = \frac{m_h}{m_\ell} \times \frac{F_h(p-z-\psi\Delta_h^w(p,z))}{F_\ell(p-z)}$. Thus, the intermediate likelihood ratio ρ for each type of consumer depends on $\Delta_h^w = w_h^I - w_h^U$, and in turn (as shown in Proposition 2), each of w_h^I and w_h^U depend on ρ.

Given a price for bank payment services p and an incremental value of bank payment services over the next best alternative $z \in \{v, 0\}$, define a mapping ϕ from potential values of Δ_h^w to realized values of Δ_h^w as follows. Let x denote a real-valued number that is a potential value of Δ_h^w. Given $\Delta_h^w = x$, determine the intermediate likelihood ratios for bank customers ($\rho^B(x)$) and non-customers ($\rho^N(x)$). From these likelihood ratios, in turn determine the expected loan surplus earned by the high credit type who uses the bank for payment services. This surplus is determined using equation (11) as

$$w_h^I(\rho^B(x), \alpha) \quad = \quad \left(\frac{\theta_h}{\theta_\ell} - 1\right) \frac{\lambda}{2} \left(\frac{\alpha}{1+\alpha} q_\ell(\rho^B(x)\alpha)^2 + \frac{1}{1+\alpha} q_\ell(\rho^B(x)/\alpha)^2\right), \tag{17}$$

after taking into account the probabilities of generating signals s_h and s_ℓ. Similarly, the loan surplus earned by the high credit type who uses the alternative payment technology is given by equation (14), and may be written as

$$w_h^U(\rho^N(x)) = \left(\frac{\theta_h}{\theta_\ell} - 1\right) \frac{\lambda}{2} \left(q_\ell(\rho^N(x))\right)^2 \tag{18}$$

Denote $\phi(x) = w_h^I(\rho^B(x), \alpha) - w_h^U(\rho^N, \alpha)$. Then, a fixed point of $\phi(x)$ represents a value of Δ_h^w that is internally consistent; given that value of Δ_h^w, the demand for bank payment services across the two credit types is such that indeed the incremental loan surplus from using the bank for payment services works out to Δ_h^w. We first show that the mapping $\phi(\cdot)$ has a unique fixed point, which establishes that the bank's demand function for payment services is well-defined.

Lemma 2. *For each price p for bank payment services and each $z \in \{v, 0\}$, the mapping $x \mapsto \phi(\cdot)$ has a unique fixed point.*

Given that the cost of providing payment services is zero, the bank's total profit, including its revenue from payment services and its profit from loans, is

$$\Pi = \sum_{j=h,\ell} m_j \left[(1 - F_j(p^m - v - \psi\Delta_j^w))(p^m + \psi\pi_j^I) + F_j(p^m - v - \psi\Delta_j^w)\psi\pi_j^U \right]. \tag{19}$$

In what follows, we assume the second-order condition for profit maxmization holds and the optimal price is unique. We verify this condition in our numerical examples.

While standard intuition is that competition lowers prices, we provide sufficient conditions for the price of bank payment services to either increase or decrease in the face of FinTech competition, compared to when the bank is the only payment service provider. In particular, we consider the special case that the bank affinity distribution is the same for both credit types. Note that even in this case, different proportions of high and low credit type use the bank for payment services, and the choice of payment provider is informative about credit type. That is, the endogenous threshold consumer of each credit type indifferent between using the bank and not, $b_j^m(p)$ or $b_j^c(p)$ as the case may be, differs across the two credit types θ_h and θ_ℓ. This point can be observed by noting that $\Delta_\ell^w = 0$ and that in general $\Delta_h^w \neq 0$ in the expression for the threshold consumer in Lemma 1.

Proposition 3. *Suppose the bank affinity distribution F_j is the same for each $j = h, \ell$, so that $F_h(b) = F_\ell(b) = F(b)$ for all b. Then, there exists a $\bar{\psi} > 0$ such that, for each $\psi < \bar{\psi}$,* *comparing the case in which FinTech firms compete with the bank in payment services to the case in which the bank is a monopolist payment processor,*

(i) The bank's price for payment services decreases if the bank affinity distribution F has an increasing hazard rate throughout.

(ii) The bank's price for payment services increases if the bank affinity distribution F has a decreasing hazard rate throughout.

In the industrial organization literature, Chen and Riordan (2008) characterize conditions under which the price of a good can be higher under duopoly than under monopoly. The trade-off is essentially between increasing market share (which induces a lower price) and operating at an inelastic segment of the demand curve (which could induce a higher price). In our framework, the demand the bank faces is determined by both the price of its payments services but also the consumers' equilibrium perception of the surplus from a loan.

The technical condition of an increasing or decreasing hazard rate has its roots in the standard pricing problem of a monopolist. To illustrate the intuition, suppose $\psi = 0$, and consider the simplified problem of a monopolist bank maximizing its profit in the payment market alone when $F_h = F_\ell = F$. The demand for payment services is $1 - F(p - z)$, where $z = v$ when the bank is a monopolist. The bank's profit is $(1 - F(p - z))p$. The first-order condition for the optimal price is $1 - F(p - z) - f(p - z)p = 0$, so that

$$H(p - z)p = 1, \tag{20}$$

where $H(p - z) = \frac{f(p-z)}{1-F(p-z)}$ is the hazard rate of the bank affinity distribution. Assuming the second-order condition is satisfied, let p^m be the optimal price of a monopolist.

Competition by FinTech firms moves z from v to 0. If the hazard rate $H(\cdot)$ is decreasing, we have $H(p) < H(p - v)$ for all p. Thus, $H(p^m)p^m < 1$, and the optimal price must set

$p^c > p^m$. The logic is reversed if $H(\cdot)$ is decreasing. If the hazard rate is constant, then $p^c = p^m$.

In Proposition 3, we assume there is a low probability that a consumer needs a loan. We show through a numerical example that even when (i) the affinity distributions are different for the high and low credit types and (ii) the probability a consumer needs a loan (ψ) is high (set to 1 in our example), the bank's price for payment services can increase with competition. We fix the bank affinity distribution for the low credit type consumer to be the exponential distribution, and for the high credit type consumer to be a Weibull distribution.[16] We vary the first parameter of the Weibull distribution k between 0.5 and 1.5, and set the second parameter λ to be 1. When $k < 1$, the distribution has a decreasing hazard rate, and when $k > 1$ it has an increasing hazard rate. Figure 2 shows the prices both when the bank is a monopolist in payment services and when it competes with the FinTech firms. As can be seen from the figure, when the hazard rate for the high credit type is decreasing, the price under FinTech competition is greater than the monopoly price, with the converse being true with an increasing hazard rate.

4.1 Welfare Effects of FinTech Competition

FinTech competition in payments affects both consumer welfare and the overall surplus in our model through three channels: (i) the presence of FinTech pulls cash users into the payment system (financial inclusion), (ii) the change in the bank's price for payment services directly affects the welfare of consumers with high bank affinity (who remain with the bank), and (iii) there is an indirect effect on welfare through the loan market, as the bank's beliefs about both payment customers and non-customers changes with FinTech entry, which affects the menu of loan contracts the bank offers.

[16] The Weibull distribution, which includes the exponential distribution as a special case, satisfies the assumption that $\lim_{p\to\infty} p(1 - F(p)) = 0$ made in Proposition 3. The distribution function for the Weibull distribution is $F(x \mid k, \lambda) = 1 - e^{-(x/\lambda)^k}$, where k and λ are parameters of the distribution.

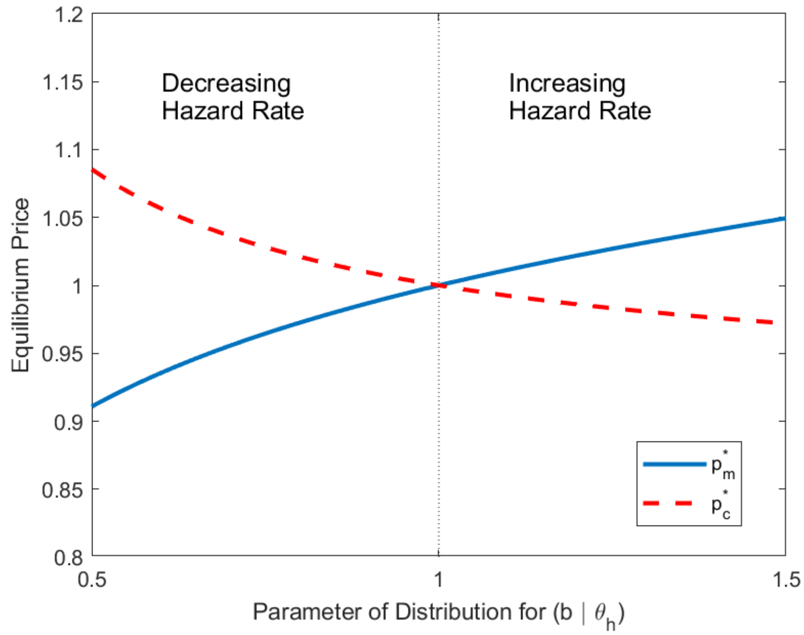


Figure 2: **FinTech Competition can lead to higher or lower prices for the bank's payment services.**
Here, $A = 2, \theta_h = 0.99, \theta_\ell = 0.95, \lambda = 0.4, \gamma = 0.2, \psi = 1, \alpha = 2, m_h = m_\ell = 0.5$. The bank affinity distribution for type ℓ is exponential. The bank affinity distribution for type h is Weibull, with first parameter k varying from 0.5 to 1.5, and the second parameter set to $\lambda = 1$. The solid line p^*_m shows the optimal price for bank payment services when the bank is a monopolist, and the dashed line p^*_c is the corresponding price when FinTech firms compete with the bank.

The first effect is positive—the welfare of low bank affinity consumers improves after FinTech entry due to access to electronic payments. From Proposition 3 and Figure 2, the second effect may be positive or negative. In particular, the bank's price for payment services can increase after FinTech entry, which hurts high bank affinity consumers, who are bank payment customers even after FinTech entry. The third effect, the welfare in the loan market, also may increase or decrease with FinTech competition.

The interaction of these three effects implies that the total impact of FinTech competition is generally nuanced and ambiguous. Nonetheless, there are a few clear predictions from the model, as summarized in the following proposition.

Proposition 4. *Comparing the cases of FinTech competition in payments to the bank being a monopolist in payments,*

(i) The profit of the bank is strictly lower.

(ii) The total surplus from loans to high credit type consumers is unchanged.

(iii) Among low credit type consumers,

(a) Those with low bank affinity $b < \min\{b_c(p_c^*), b_m(p_m^*)\}$ strictly benefit from financial inclusion.

(b) Those with high bank affinity $b > \max\{b_c(p_c^*), b_m(p_m^*)\}$ benefit if $p_c^* < p_m^*$, and are hurt if $p_c^* > p_m^*$.

Part (i) of Proposition 4 predicts an unambiguous reduction in total bank profit following FinTech competition. This is unsurprising but also nontrivial because FinTech competition generally has an ambiguous impact on the bank's price for payment services and on loan market outcomes. For parts (ii) and (iii), recall that loans to high credit type consumers always have the first-best quantity, so the total surplus of such loans between the borrower and the lender is not affected by FinTech competition. In comparison, low credit type consumers always get zero surplus from the loan market, so the utility of those who stay with the bank depends only on the price of payment services.

The total surplus from loans to low credit types and the consumer surplus accruing to high credit types are generally ambiguous. To illustrate, we consider a numerical example. The details of the example are presented in Appendix C. In the example, we use different distributions for bank affinity for the high and low credit types, and show how the relative shape of these distributions affects the welfare implications of FinTech entry. The main conclusions that emerge from the example may be summarized as follows.

Observation 1. *(i) The expected loan surplus obtained by high credit type consumers may increase or decrease after FinTech entry.*

(ii) The total surplus from loans to low credit consumers may increase or decrease after FinTech entry.

Broadly, if FinTech competition leads to a sufficiently greater proportion of high credit types using the bank for payment services, high credit types who remain bank customers obtain worse loan terms. Conversely, if FinTech competition results in proportionately more low credit types using the bank's payment services, high credit types who remain bank customers obtain better loan terms. The effects on bank non-customers similarly depend on how FinTech competition affects the mix of high and low credit types who stay away from the bank in the payment market. As before, the overall surplus from a loan to low credit types is inversely related to the loan surplus obtained by the high credit type.

Next, consider the comparative statics in α, the precision of the signal extracted from payment data. As $\alpha \to \infty$, in the limit the type of the consumer is fully revealed. At this point, the high credit type obtains zero surplus from a loan, and the total surplus from a loan to the low credit type is equal to the first-best surplus. More generally, for many parameter values, when the bank is informed the expected loan surplus of the high credit type is decreasing in α. The intuition is that when the bank knows that a given consumer is more likely to be the high type, it can extract greater surplus from the consumer.

However, there are also cases in which the high credit type's loan surplus increases in α. Suppose that the ex ante probability of high credit borrowers is very high, and consequently, they receive a very small loan market surplus to start with. Then, the high signal from payment data has little effect on the menu of contracts offered, and hence little effect on the loan surplus to the high credit type. Conversely, the low payment signal can have a relatively large (and positive) effect on this surplus. Although the likelihood of the low signal decreases in α, the overall effect may still be that the loan surplus to the high credit type increases in α. Figure 3 provides such an example.

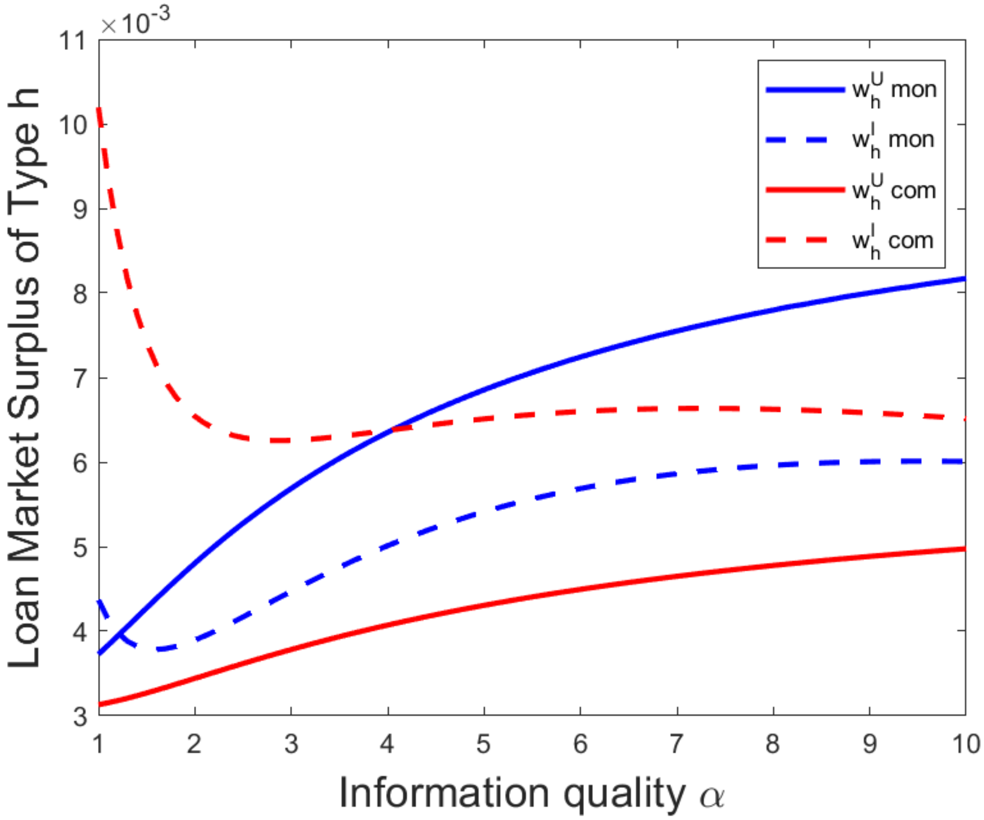


Figure 3: **Expected Loan Surplus of High Credit Type**
This figure plots the expected loan surplus captured by credit type θ_h for different parameter values and payment market structures. Here, $A = 2, \theta_h = 0.99, \theta_\ell = 0.8, \lambda = 0.4, \gamma = 0.2, \psi = 1, \alpha = 2, m_h = 5, m_\ell = 0.5$. The bank affinity distribution for credit type θ_ℓ is exponential, and for credit type type θ_h is Weibull with first parameter $k = 2$ (so the hazard rate is increasing). For each set of parameters, we find the optimal price for bank payment services. The blue lines indicate the bank is a monopolist in payment services, and the red lines that the bank faces FinTech competition. The solid lines indicate the bank is uninformed about the consumer, and the dashed lines that the bank is informed.

In summary, when FinTech competes with banks for core banking services it can affect consumer welfare through three possible channels. First, FinTech competition can increase financial inclusion. Consumers who find it costly to form a relationship with a bank are given access to electronic payments. Second, banks will reprice their core banking services. As we have shown it is possible for payment prices to increase or decrease as a result of changes in the mix of customers. Finally, FinTech competition affects the flow of information in the economy. Consumers may choose to move their payments away from the bank because of the cheaper payment alternative, which affects information in the loan market.

5 Using Non-Bank Payment Data for Bank Lending

We now consider one market-based and one regulatory outcome under which information obtained from payments processed by FinTech firms may flow back to the bank and be used in lending.

5.1 FinTechs Sell Data to Bank

Suppose that there is a private data market in which the stand-alone FinTech firms sell customer data to the loan provider (the bank). Various institutional arrangements are consistent with an active data market. In particular, our data sales regime is consistent with the widespread practice of banks and FinTech firms forming partnerships in which banks provide capital and FinTech firms provide the user interface and data analytics.

To simplify the actual institutional arrangement in the data sales market, we assume that the bank and each FinTech firm agree in advance on a fixed price for the data of each consumer. In terms of the timeline in Figure 1, the first stage at $t = 1$ is a negotiation between the bank and the FinTech firms over the price of data per consumer. The new timeline is shown in Figure 4.

It is immediate that, all else equal, access to payment data makes the bank strictly better off whenever $\alpha > 1$. Therefore, there exists a price $y > 0$ for data transferred by a FinTech firm to the bank such that both the FinTech firms and the bank are willing to participate in the data sales market. We do not model the exact negotiation details between the bank and

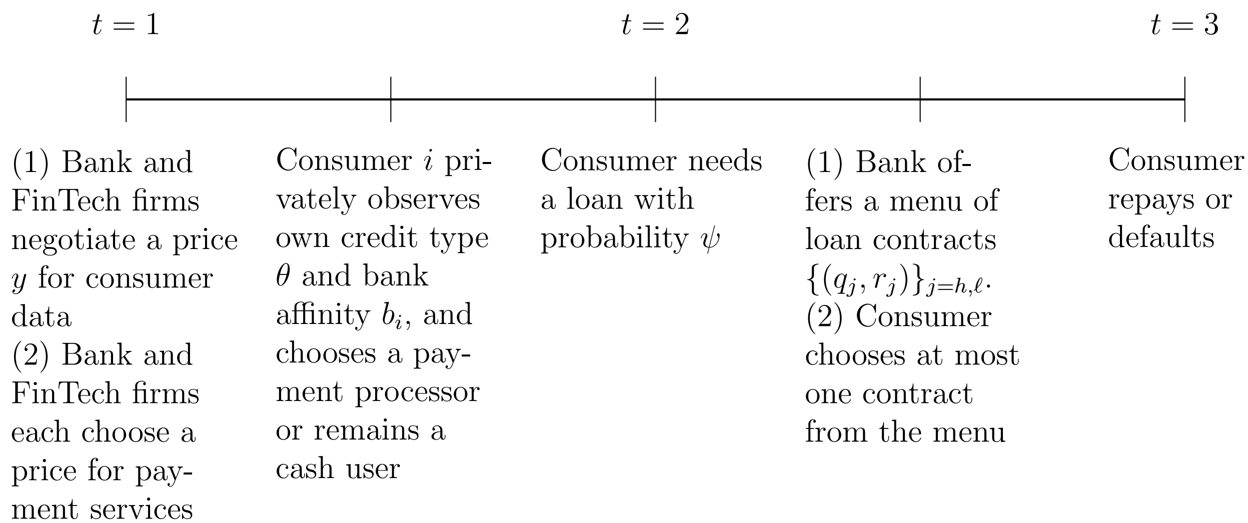


Figure 4: **Timing of Events with FinTech Data Sales**

a FinTech firm. Instead, we take the price for data y as given, and analyze the implications of the bank having access to payment data from FinTech consumers.

From the FinTech point of view, each payment customer generates data that it can sell with probability ψ. Given Bertrand competition, this extra revenue will induce the FinTech firms to cross-subsidize their payments. Thus, the FinTech payment price becomes $-\psi y$ per consumer. In other words, the FinTech customers receive "freemium" products which they value that also generate data.

The equilibrium with data sales can be solved in a similar fashion as before. Let b_j^s denote the bank affinity value of a consumer with credit type θ_j who is indifferent between choosing the bank and a FinTech firm for payment services, where the superscript s means data sales. Whichever payment service the consumer chooses, the bank is informed about their payment history at the time they seek a loan. Recall from Proposition 2 that the expected consumer surplus earned by a high credit type from a loan, w_h^I, depends on both the likelihood ratio of a high-versus-low credit type before the payment signal is obtained, ρ, and the precision of the signal from payments, α. Let ρ^{FT} denote the likelihood ratio for a FinTech consumer, and ρ^B the corresponding ratio for a bank consumer, before the signal from payments is extracted. Then, b_j^s satisfies

$$v - p + b_j^s + w_j^I(\rho^B, \alpha) = v + \psi y + w_j^I(\rho^{FT}, \alpha) \quad (21)$$

$$b_j^s(p) = p + \psi y + (w_j^I(\rho^{FT}, \alpha) - w_j^I(\rho^B, \alpha)). \quad (22)$$

A consumer with bank affinity $b > b_j^s$ ($b < b_j^s$) chooses the bank (a FinTech firm) for payment processing.

The bank is now informed about all loan applicants. Given the price of buying consumer data from a FinTech firm, y, the bank chooses its payment services price p to maximize

$$\Pi^s = \sum_j m_j \Big[(1 - F_j(b_j^s(p)))(p + \psi\pi_j^I(\rho^B, \alpha)) + F_j(b_j^s(p))(\psi\pi_j^I(\rho^{FT}, \alpha) - y)\Big]. \quad (23)$$

We show that in the special case that the bank affinity distribution is the same for both credit types, the relative mass of high versus low credit types that uses each payment service (bank or FinTech) is the same. The further implication is that there is no difference in the contract menu offered to bank and FinTech payment customers.

Proposition 5. *Suppose the bank affinity distribution is the same across the two credit type θ_h and θ_ℓ, that is, $F_h(b) = F_\ell(b)$ for all b. Then, for every consumer data price y and bank price for payment services p:*

(i) $b_h^s(p) = b_\ell^s(p)$, so that the demand for bank services, $1 - F_j(b_j(p))$, is the same across the two credit types.

(ii) $\rho^B = \rho^{FT} = \frac{m_h}{m_\ell}$. That is, whether a consumer is a bank or FinTech payment customer does not convey any information about their credit type.

The arguments in Proposition 3 can be extended to the data sales case to show that the price for the bank's payment services may increase or decrease when data sales occur, compared to the price in the base model with FinTech competition but without data sales. As a result, the welfare effects of data sales are nuanced. The presence of a data market introduces changes to the welfare of both low and high bank affinity consumers.

Low bank affinity consumers benefit from the payment subsidy provided by the FinTech firm, $-\psi y$. The size of this subsidy depends on the price y negotiated between the bank and the FinTech firms.[17] The latter outcome is qualitatively similar to a data tax, which the government could collect from the data sales transaction and reimburse to FinTech consumers.

The loan offers received by consumers are different when the bank obtains the payment signal about FinTech consumers. As in Section 4, high credit type consumers' loan market surplus can go up or down, whereas low credit type consumers' loan market surplus still stays at zero.

High bank affinity consumers see a change in both the price for banking payment services and the loan offers they receive. The latter occurs because the presence of FinTech data sales affects the sorting of consumers into bank payment customers and non-customers, which in turn affects the bank's beliefs about their payment customers. As a result of these two effects, high bank affinity consumers may be better off or worse off, regardless of their credit type.

Observation 2. *Comparing FinTech sales of data to the base model with FinTech competition but no data sales:*

(i) Overall expected surplus from the loan market is greater.

(ii) Consumers with low bank affinity and the low credit type are strictly better off with FinTech sales of data.

[17] An important assumption we make is that the FinTech firms make zero profit in expectation and pass the entire price for data sales back to consumers. If the FinTech firms were imperfectly competitive, only part of the data sales revenue would be passed to consumers.

(iii) Any of the following consumer groups, {high bank affinity, high credit type}, {high bank affinity, low credit type}, and {low bank affinity, high credit type}, may be better off or worse off.

Thus, although the standard intuition in economics is that introducing a missing market alleviates an externality, the welfare effects of allowing the FinTech firm to provide data to the bank are nuanced. In any equilibrium in which data sales occur, the bank earns a higher profit than without data sales. However, consumer welfare may be higher or lower. The fact that the high credit type consumers who use a FinTech firm for payments can be worse off in the presence of an information market provides a micro-foundation for a preference for privacy.

One interpretation of FinTech competition for payment customers and hence data is that the FinTech company is a mechanism for the consumer to extract rents from the bank in exchange for their data. As a vertically integrated payments and lending company, the bank partially internalizes the benefit of data. By contrast, competing FinTech firms directly pass the market value of data back to the consumers through a payment subsidy.

5.1.1 FinTechs Process Data for the Bank

If the FinTech firms have a superior data analysis technology compared to the bank, then instead of selling raw payment data to the bank, the FinTech firm can sell the data processing technology to the bank so the bank can extract better signals from its own customers' payment data. The superior data processing capability of the FinTech firms can be thought of as an increase in α, the precision of the signal from payment data.

It turns out that such a data processing arrangement will lead to an outcome similar to that in data sales, in the sense that when a consumer applies for a loan, the bank always has access to the signal from payments. The difference is that the signal is provided by the FinTech firm. Therefore, a FinTech firm can earn revenues from the bank both for data sales on FinTech payment customers and for data processing on bank payment customers. If FinTech firms are perfectly competitive, as in our model, the fees they charge for processing data would be their cost of doing so. Compared to the base model in which information on FinTech customers is lost to the bank, the welfare effects are similar to those for data sales.

5.2 Consumers Own and Port Their Data

Suppose that consumers control their own data, and can provide a credible record of their payment history to a lender. Formally, in terms of the timeline in Figure 1, at $t = 2$ if a consumer needs a loan, the bank asks the consumer to share their payment history data. The consumer may then either share it or decline, following which the bank chooses a menu of contracts for the consumer. Thus, at the time of making a loan, the bank is potentially faced with three kinds of consumers: those with high payment signals, those with low payment signals, and those who have declined to share their payment history. In accordance with Proposition 2, for each kind of consumer the bank will design a menu of separating contracts, one contract for the high credit type and another for the low credit type.

The key question is whether voluntary data porting actually leads to consumers providing their data to the bank. We answer in the affirmative. Because the bank makes a positive profit on each credit type, the bank can offer loan applicants an infinitesimal inducement $\epsilon > 0$ if they provide their payment history data to the bank. The low credit type obtains zero surplus from the loan regardless of what they do, so will strictly prefer to provide their data. At that point, any FinTech customers who decline to provide their data are easily inferred to be the high credit type, and the monopolist bank can extract all the surplus generated by a loan. Notice that if the high credit type also provides their data, the bank cannot perfectly infer the credit type, as the payment signal remains noisy. The high credit type is thus better off also providing their data. In equilibrium, all consumers willingly port their data to the bank. In the limit as $\epsilon \to 0$, it remains an equilibrium for all consumers to share their data with the bank. The nature of this equilibrium is reminiscent of unraveling. By sharing data, consumers impose a *data externality* on everyone else. The externality is strong enough that everyone shares data.

In what follows, we restrict attention to the equilibrium in which all consumers port their data to the bank at no cost to the bank. In the absence of an inducement to deliver their data, the low credit type is indifferent between giving their data to the bank and not doing so. Thus, depending on parameters, there may also exist an equilibrium in which no FinTech consumer transfers their data to the bank. However, this equilibrium is not robust to infinitesimal inducements.

The bank's optimal price for payment services can be derived in a similar fashion as the case of data sales. Let b_j^o be the cutoff bank affinity value of credit type j under data porting, or open banking. Because data are shared for free, the marginal consumer's calculation is

$$\begin{aligned} v - p + b_j^o + w_j^I(\rho^B, \alpha) &= v + w_j^I(\rho^{FT}, \alpha) && (24) \\ b_j^o(p) &= p + (w_j^I(\rho^{FT}, \alpha) - w_j^I(\rho^B, \alpha)). && (25) \end{aligned}$$

A consumer with bank affinity $b > b_j^o$ ($b < b_j^o$) chooses the bank (a FinTech firm) for payment processing. In particular, because low credit type consumers always get zero surplus in the loan market, we have $b_\ell^o = p$.

Likewise, the bank's profit is

$$\Pi^o = \sum_j m_j \Big[(1 - F_j(b_j^o(p)))(p + \psi \pi_j^I(\rho^B, \alpha)) + F_j(b_j^o(p)) \psi \pi_j^I(\rho^{FT}, \alpha) \Big]. \tag{26}$$

By this point, it is transparent that consumers owning and voluntarily porting data is a special case of FinTech data sales, with $y = 0$. Intuitively, if FinTech firms sell consumer data at a zero price, it is equivalent to consumers porting data at a zero price. Therefore, when compared to the base case with FinTech competition but without data transfer, most qualitative effects of FinTech data sales also apply to data porting. In particular, the overall loan market surplus goes up due to information sharing, but the high credit type's loan surplus may increase or decrease. Also, the price for payment services may go up or down.

Between data sales and data porting, which one is better for consumers? In this economy, consumer surplus comes from payment services and loans. Low credit type consumers always receive zero surplus in the loan market. If the distribution of bank affinity is identical between high and low credit types, as in Proposition 5, high credit type consumers also receive the same surplus between data sales and data porting. This is because in both cases, the equilibrium mix between the two credit types is identical to the prior, m_h/m_ℓ, and the bank observes the consumer's payment data when borrowing. Therefore, the comparison in consumer welfare rests entirely on the price of payment services. The following proposition shows conditions under which the bank's payment services under data sales is strictly better than that under (free) data portability.

Proposition 6. *Suppose that: (i) the bank affinity distribution is the same across the two credit types, i.e., $F_h(b) = F_\ell(b) = F(b)$ for all b, and (ii) under data sales, the bank and each FinTech firm negotiate a price for FinTech data sales $\hat{y} > 0$. Then:*

(i) The loan market outcomes are identical under data sales and under data portability.

(ii) Both the bank and the FinTech firms have a strictly lower price for payment services under FinTech data sales than under consumer data portability.

Consequently, all consumers strictly prefer data sales to data portability.

The intuition behind Proposition 6 is straightforward. Under FinTech data sales, consumers receive a fraction of the value of their data in the form of subsidized payments from

FinTech firms. Thus, the bank needs to offer better prices to entice consumers to use the bank. But if data are ported for free, the bank no longer has such an incentive, and the price worsens.

To gain further intuition, we can write the bank's profit with data porting, given $F_h = F_\ell = F$ and $\rho^B = \rho^{FT}$, as

$$\Pi^o = \sum_j m_j \left[(1 - F(p))p + \psi \pi_j^I (\frac{m_h}{m_\ell}) \right] = (1 - F(p))p + \sum_j m_j \psi \pi_j^I (\frac{m_h}{m_\ell}). \tag{27}$$

The second term in the profit expression, which comes from loans, has nothing to do with the price of payment services, that is, there is a complete decoupling of payment and credit if data are ported for free. The full decoupling does not happen under data sales because the bank's profit given $F_h = F_\ell = F$ is

$$\Pi^s = \sum_j m_j \left[(1 - F(p + \psi y))p + \psi \pi_j^I (\frac{m_h}{m_\ell}) - \psi F(p + \psi y) y \right], \tag{28}$$

where the last term is the cost of purchasing data from FinTech firms. In general, $(1-F(p+\psi y))p - \psi F(p + \psi y)y \neq (1 - F(p))p$.

The results of this section highlight a data externality. In the presence of data transfers, consumer welfare from the loan depends on their bargaining power relative to the bank. Data sales are equivalent to the FinTech firm negotiating with the bank on behalf of a block of consumers, whereas with data porting the bank is able to "divide and conquer" consumers in one-on-one negotiations. While the data externality seems stark in our two-credit-type setting, we expect it to be a more general phenomenon even with $N > 2$ credit types. As before, the bank is able to induce data sharing from the lowest credit type consumers. Once the lowest type is revealed, the bank can use the same inducement on the lowest of the remaining $N - 1$ types. So on it goes, and unraveling ensues.

Our results on consumers owning their data contrast with those of Jones and Tonetti (2020), who argue that "giving data property rights to consumers can generate allocations that are close to optimal." However, their framework features a representative agent and thus homogeneous consumers. Our heterogeneous-agent framework leads to different results.

6 Conclusion

New data processing technology has increased the economic importance of data. Banks, through their joint role as payment processors and financial service providers, have long enjoyed privileged access to consumers' and firms' transaction data. We provide a flexible framework that points to the complex effect that the loss of these data will have on both the payments and financial services markets. Our analysis suggests that policy-makers should take a nuanced and country-specific approach to FinTech competition.

There is still much work to be done to understand the optimal way in which control rights to our large and growing data footprints should be allocated. In our framework, a data market is always weakly preferred to consumer data portability. This result is due to market power: with data sales, a FinTech firm negotiates with the bank to extract part of the market value of the data which it then reimburses to consumers. If multiple banks competed for the data, presumably the FinTech firm would extract more of the value. By contrast, individual consumers, each lacking market power, cannot do so. To the extent that FinTech market power also becomes a concern—which it has, outside our model—could a social planner do better by establish a data warehouse and negotiating on behalf of consumers?

A Table of Notation

θ_j, for $j = h, \ell$	Consumer's repayment probability
v	Consumer's value for using electronic payment rather than cash
b	Consumer's bank affinity; negative b means a cost to access the bank
F, f	Distribution and density of consumer's bank affinity
ψ	Probability that a consumer needs a loan in period 2
(q, r)	Loan quantity and interest rate offered by the bank
α	Quality of the signal about a consumer's credit type extracted from payment data
w_j^U	Consumer surplus to credit type θ_j from the loan when the bank is uninformed
w_j^I	Expected consumer surplus to credit type θ_j from the loan when the bank is uninformed
Δ_h^w	Expected change in consumer surplus from the loan for credit type θ_h when the bank is informed, compared to when the bank is uninformed
π_j^U	Bank's expected profit from making a loan to credit type θ_j when the bank is uninformed
π_j^I	Bank's expected profit from making a loan to credit type θ_j when the bank is informed
p	Price charged by bank for payment services
b^*	Threshold bank affinity of consumer who is indifferent between using the bank for payment services and the alternative (depending on the case being considered, the alternative is to remain unbanked or to use the FinTech firm for payment services)
y	Price per consumer at which data are sold by FinTech firm to bank
^{m}	Superscript, benchmark case in which the bank is a monopolist provider of payment services
^{c}	Superscript, base case in which FinTech firms compete with the bank in providing payment services
^{s}	Superscript, case in which FinTech firms can sell data to banks
^{o}	Superscript, case in which consumers own and port data

B Proofs

B.1 Proof of Proposition 1

We proceed with a series of steps.

Step 1: At least one of the constraints IR_h and IR_ℓ must bind.

Suppose not, so that we have an optimum in which both IR constraints are slack. Then, there are two sub-cases to consider.

(i) One of the IC constraints is slack. Then, we can find a suitable increase in each of r_ℓ and r_h such that the binding IC constraint is strictly satisfied, the slack IC constraint continues to hold, and the IR constraints hold. This contradicts the assumption that we are at an optimum.

(ii) Both IC constraints bind. Observe that we can write $w(q, r \mid \theta) = \theta\{Aq - q(1+r) + \frac{\lambda}{2}q^2\} - \frac{\lambda}{2}q^2$. Therefore, the binding IC constraints IC_h and IC_ℓ can respectively be written as:

$$
\begin{aligned}
Aq_h - q_h(1+r_h) + \frac{\lambda}{2}q_h^2 - \frac{1}{\theta_h}\frac{\lambda}{2}q_h^2 &= Aq_\ell - q_\ell(1+r_\ell) + \frac{\lambda}{2}q_\ell^2 - \frac{1}{\theta_h}\frac{\lambda}{2}q_\ell^2 \qquad (29)\\
Aq_\ell - q_\ell(1+r_\ell) + \frac{\lambda}{2}q_\ell^2 - \frac{1}{\theta_\ell}\frac{\lambda}{2}q_\ell^2 &= Aq_h - q_h(1+r_h) + \frac{\lambda}{2}q_h^2 - \frac{1}{\theta_\ell}\frac{\lambda}{2}q_h^2 \qquad (30)
\end{aligned}
$$

Summing the two inequalities and simplifying, we have

$$
\frac{1}{\theta_h}(q_h^2 - q_\ell^2) \;\geq\; \frac{1}{\theta_\ell}(q_h^2 - q_\ell^2). \qquad (31)
$$

As $\theta_h > \theta_\ell$, it must be that $q_h = q_\ell$. This further implies that $r_h = r_\ell$ (or the IC constraint must be violated for at least one type), so the contract is a pooling contract.

Now, if the contract is a pooling contract and both IR conditions are slack, it is immediate that a small increase in r_h and r_ℓ, increasing both by the same amount, leads to an increase in profit for the lender while preserving all constraints. Again we have a contradiction that the original contract was optimal.

Therefore, at the optimum contract, at least one IR constraint must bind.

Step 2: Optimal contract when IR_ℓ binds.

Suppose IR_ℓ binds at the optimal contract. Then $\theta_\ell(1+r_\ell)q_\ell = \theta_\ell A q_\ell - (1-\theta_\ell)\frac{\lambda}{2}q_\ell^2$. Therefore,

$$w_h(q_\ell, r_\ell) \quad = \quad \theta_h A q_\ell - \frac{\theta_h}{\theta_\ell}\Big(\theta_\ell A q_\ell - (1-\theta_\ell)\frac{\lambda}{2}q_\ell^2\Big) - (1-\theta_h)\frac{\lambda}{2}q_\ell^2 = \Big(\frac{\theta_h}{\theta_\ell} - 1\Big)\frac{\lambda}{2}q_\ell^2. \quad (32)$$

Hence, $w_h(q_\ell, r_\ell) > 0$. From IC_h, it follows immediately that $w_h(q_h, r_h) > 0$, so IR_h is slack.

Suppose also that IC_h is slack at the optimal contract. Then, for a small enough increase in r_h, IC_h and IR_h continue to hold, and the RHS of IC_ℓ is reduced, so IC_ℓ must continue to hold. There is no effect on IR_ℓ. The increase in r_h strictly increases the bank's profit, so the contract could not have been optimal. Thus, it must be that IC_h binds at the optimum. IC_h binding implies that $w_h(q_h, r_h) = w_h(q_\ell, r_\ell) = \Big(\frac{\theta_h}{\theta_\ell} - 1\Big)\frac{\lambda}{2}q_\ell^2$.

Now, the bank's profit is

$$\Pi \quad = \quad \sum_{j=h,\ell} \mu_j \Big\{\theta_j(1+r_j)q_j - q_j - \frac{\gamma}{2}q_j^2\Big\}. \quad (33)$$

As noted above, IR_ℓ binding implies that $\theta_\ell(1+r_\ell)q_\ell = A\theta_\ell q_\ell - (1-\theta_\ell)\frac{\lambda}{2}q_\ell^2$. Further, from the binding IC_h constraint, we can write $\theta_h(1+r_h)q_h = A\theta_h q_h - (1-\theta_h)\frac{\lambda}{2}q_h^2 - \frac{\lambda}{2}\Big(\frac{\theta_h}{\theta_\ell} - 1\Big)q_\ell^2$. Substituting these expressions into the profit function,

$$\begin{aligned} \Pi \quad = \quad & \mu_\ell \Big\{A\theta_\ell q_\ell - (1-\theta_\ell)\frac{\lambda}{2}q_\ell^2 - q_\ell - \frac{\gamma}{2}q_\ell^2\Big\} \\ & + \mu_h \Big\{A\theta_h q_h - (1-\theta_h)\frac{\lambda}{2}q_h^2 - q_h - \frac{\gamma}{2}q_h^2 - \frac{\lambda}{2}\Big(\frac{\theta_h}{\theta_\ell} - 1\Big)q_\ell^2\Big\}. \end{aligned} \quad (34)$$

The first-order condition in q_h yields

$$q_h^* \quad = \quad \frac{A\theta_h - 1}{\gamma + (1-\theta_h)\lambda}, \quad (35)$$

which is the first-best quantity. Similarly, the first-order condition in q_ℓ yields

$$q_\ell^* = \frac{A\theta_\ell - 1}{\gamma + \lambda\Big(1 - \theta_\ell + \frac{\mu_h}{\mu_\ell}\Big(\frac{\theta_h}{\theta_\ell} - 1\Big)\Big)} = \frac{A\theta_\ell - 1}{\gamma + \lambda(1-\theta_\ell) + \lambda\kappa\Big(\frac{\theta_h}{\theta_\ell} - 1\Big)} \tag{36}$$

It is immediate to see that in each case the second-order condition is satisfied.

We have shown that IR_h is satisfied; what remains is to check IC_ℓ. As $w_\ell(q_\ell, r_\ell) = 0$, IC_ℓ here reduces to $w_\ell(q_h, r_h) \leq 0$, or $\theta_\ell A q_h - \theta_\ell(1 + r_h)q_h - (1-\theta_\ell)\frac{\lambda}{2}q_h^2 \leq 0$.

From the binding IC_h constraint, we obtain:

$$\theta_\ell(1+r_h)q_h = \frac{\theta_\ell}{\theta_h}\,\theta_h(1+r_h)q_h = \theta_\ell A q_h - \theta_\ell\left(\frac{1}{\theta_h} - 1\right)\frac{\lambda}{2}q_h^2 - \frac{\lambda}{2}\Big(1 - \frac{\theta_\ell}{\theta_h}\Big)q_\ell^2. \tag{37}$$

Substituting the RHS for the term $\theta_\ell(1+r_h)q_h)$ in $w_\ell(q_h, r_h)$, we obtain

$$w_\ell(q_h, r_h) \;=\; -\Big(1 - \frac{\theta_\ell}{\theta_h}\Big)(q_h^2 - q_\ell^2) < 0, \tag{38}$$

where the last inequality follows from $q_h > q_\ell$. To see that $q_h > q_\ell$, observe that the first-best loan quantity q^f is strictly increasing in θ. Further, the optimal contracts feature $q_h^* = q_h^f$ and $q_\ell^* \leq q_\ell^f$, so it must be that $q_h^* > q_\ell^*$.

Therefore, starting with the assumption that IR_ℓ binds, we have found a solution (q_h^*, q_ℓ^*) such that the lender's conditions for profit-maximization are satisfied, IC_h also binds, and IR_h and IC_ℓ are both satisfied as strict inequalities. It follows immediately that r_ℓ^* is chosen to satisfy IR_ℓ, and r_h^* to satisfy IC_h.

Step 3: It cannot be optimal for IR_h to bind.

Next, suppose that IR_h binds; i.e., $w_h(q_h, r_h) = 0$. Observe that for any feasible contract (q, r), the borrower's utility $w_j(q, r)$ is strictly increasing in θ_j. To see this, observe that $w_j(q, r) = \theta q\{A - (1+r) + \frac{\lambda}{2}q\} - \frac{\lambda}{2}q^2$. Now, in any feasible solution, it must be that

$1+r<A$. Otherwise, the borrower's IR constraint is violated even when $\lambda=0$, and the loan will be rejected. When $1+r<A$, it is immediate that $w_j(q,r)$ is strictly increasing in θ_j.

Now it follows that if $w_h(q_h,r_h)=0$, then $w_\ell(q_h,r_h)<0$. In conjunction with constraint IR_ℓ (which says that $w_\ell(q_\ell,r_\ell)\geq 0$), it follows that IC_ℓ is satisfied as a strict inequality.

Observe that IR_ℓ implies that $\theta_\ell(1+r_\ell)q_\ell \leq \theta_\ell A q_\ell-(1-\theta_\ell)\frac{\lambda}{2}q_\ell^2$, so that

$$\theta_h(1+r_\ell)q_\ell=\frac{\theta_h}{\theta_\ell}\,\theta_\ell(1+r_\ell)q_\ell \leq \theta_h A q_\ell-\left(\frac{\theta_h}{\theta_\ell}-\theta_h\right)\frac{\lambda}{2}q_\ell^2. \tag{39}$$

Therefore,

$$\begin{aligned} w_h(q_\ell,r_\ell) &= \theta_h A q_\ell-\theta_h(1+r_\ell)q_\ell-(1-\theta_h)\frac{\lambda}{2}q_\ell^2 \quad (40)\\ &\geq \left(\frac{\theta_h}{\theta_\ell}-1\right)\frac{\lambda}{2}q_\ell^2. \quad (41)\end{aligned}$$

As $w_h(q_h,r_h)=0$ when IR_h binds, to satisfy IC_h it must be that $q_\ell^*=0$. The solution in this case therefore has $q_h^*=\frac{A\theta_h-1}{\gamma+\lambda(1-\theta_h)}=q_h^f$, and r_h chosen so that $w_h(q_h,r_h)=0$. Further, $q_\ell^*=0$, and we can arbitrarily set $r_\ell^*=0$.

Now, observe that the solution above is a feasible solution when maximizing the profit function in equation (34) in the previous step. However, as shown above, this solution is inferior to the optimal solution of $q_h^*=q_h^f$ and $q_\ell^*=\frac{A\theta_\ell-1}{\gamma+\lambda(1-\theta_\ell)+\lambda\kappa\left(\frac{\theta_h}{\theta_\ell}-1\right)}$, with r_ℓ^* chosen to make IR_ℓ bind and r_h^* chosen to make IC_h bind.

Therefore, it cannot be optimal for IR_h to bind.

Step 4: Optimal contract.

It now follows from the above analysis that the optimal contract is the one found in Step 2, with the constraints IR_h and IC_ℓ binding. This contract is exhibited in the statement of the proposition. ■

B.2 Proof of Proposition 2

(i) (a) Consider bank payment customers. Observe from Proposition 1 that the loan contract menu offered by the bank has $w_\ell(q_\ell, r_\ell) = 0$. That is, the low credit type obtains a zero surplus, or $w_\ell^I = 0$.

The total surplus generated by the loan to a low credit type depends on the payment signal obtained by the bank, $s \in \{s_h, s_\ell\}$. For a given signal s, this total surplus is given by $Aq_\ell^I(\kappa(s)) - q_\ell^I(\kappa(s))(1 + r_\ell^I(\kappa(s))) - \frac{\gamma+\lambda(1-\theta_\ell)}{2}(q_\ell^I(\kappa(s)))^2$. Conditional on the consumer being a low credit type, the expected surplus takes into account that the consumer generates the high signal with probability $\frac{1}{1+\alpha}$ and the low signal with probability $\frac{\alpha}{1+\alpha}$. The expected surplus may therefore be written as

$$E_s[Aq_\ell^I(\kappa(s)) - q_\ell^I(\kappa(s))(1 + r_\ell^I(\kappa(s))) - \frac{\gamma + \lambda(1-\theta_\ell)}{2}(q_\ell^I(\kappa(s)))^2 \mid \theta_\ell]. \tag{42}$$

The expected profit of the bank, π_ℓ^I, is equal to the expected surplus, as the consumer obtains zero surplus.

(b) From equation (32) in the proof of Proposition 1, a high credit type consumer obtains a surplus $w_h(q_\ell, r_\ell) = \left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{\lambda}{2}q_\ell(\kappa)^2$. Now, $q_\ell(\kappa)$, the quantity offered to the low credit type depends on the payment signal s. Further, a high type consumer generates a high signal with probability $\frac{\alpha}{1+\alpha}$ and a low signal with probability $\frac{1}{1+\alpha}$. Her expected consumer surplus may therefore be written as

$$w_h^I = \left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{\lambda}{2}\right) E_s[q_\ell(\kappa(s))^2 \mid \theta_h]. \tag{43}$$

Keeping in mind that the high credit type obtains the first-best loan quantity q_h^f, the total surplus generated by a loan to the high type given signal s is $Aq_h^f - q_h^f(1 + r_h(\kappa(s))) - \frac{\gamma+\lambda(1-\theta_h)}{2}(q_h^f)^2$. Taking an expectation over signal yields the total expected surplus, and subtracting the surplus obtained by the high credit type leads to the expression for bank profit π_h^I in the statement of the lemma.

(ii) The proof of both parts (a) and (b) when the bank is uninformed mirror the proof of the corresponding parts when the bank is informed. The expressions are simpler as in the case of the uninformed bank, the posterior likelihood ratio κ equals the intermediate likelihood ratio ρ. ∎

B.3 Proof of Corollary 2.1

Let ρ be the likelihood ratio of the high credit type versus the low credit type before the payment signal is processed. Then, the bank's expected profit from a consumer when the bank is uninformed may be written as

$$\pi^U(\rho) \quad = \quad \frac{\rho}{1+\rho}\pi_h(\rho) + \frac{1}{1+\rho}\pi_\ell(\rho). \tag{44}$$

Now, when the bank has the payment signal, it is informed, and its profit is

$$\pi^I = \frac{\rho}{1+\rho}\Big(\frac{\alpha}{1+\alpha}\pi_h(\rho\alpha) + \frac{1}{1+\alpha}\pi_h(\rho/\alpha)\Big) + \frac{1}{1+\rho}\Big(\frac{1}{1+\alpha}\pi_\ell(\rho\alpha) + \frac{1}{1+\alpha}\pi_\ell(\rho/\alpha)\Big). \tag{45}$$

Observe that if the bank offers the contract $(q_j(\rho), r_j(\rho))$ to credit type θ_j for each $j = h, \ell$, then $\pi^I = \pi^U$. Further, if the bank strictly prefers to depart from this contract (which Proposition 1 shows that it does when $\alpha > 1$), the bank earns a strictly higher profit when informed, that is, $\pi^I > \pi^U$. ∎

B.4 Proof of Lemma 1

(i) Consider a consumer with credit type θ_j and bank affinity b. Recall that w_j^I (w_j^U) represents the surplus that credit type θ_j obtains from a loan when the bank is informed (uninformed). The overall utility of the consumer from using cash is thus

$$W_j^C = \psi w_j^U. \tag{46}$$

Similarly, the overall utility from using the bank, given that p is the price of the bank's payment services is

$$W_j^B = v + b - p + \psi w_J^I. \tag{47}$$

It follows that the consumer prefers the bank to cash if and only if $W_j^B \geq W_j^C$, that is, if $b \geq b_j^m(p)$, where

$$b_j^m(p) = p - v - \psi(w_j^I - w_j^U). \tag{48}$$

The statement of part (i) now follows.

(ii) When FinTech firms enter the payment market, they compete in Bertrand fashion with each other, and so charge a price of zero. Thus, a consumer's utility from using a FinTech firm for payments is

$$W_j^{FT} = v + \psi w_j^U. \tag{49}$$

Observe that there cannot be any cash users in equilibrium. Recall that $w_\ell^I = w_\ell^U = 0$. Thus, low credit type consumers obtain utility v from using a FinTech firm and utility zero from using cash, so they strictly prefer to use a FinTech firm to using cash. Therefore, in equilibrium, any cash user must be a high credit type. But as seen from Proposition 1, when $\mu_\ell = 0$, the bank's optimal menu has $q_\ell = 0$, so credit type θ_h obtains zero surplus from the loan. If a cash-using high type deviates to a FinTech firm for payment processing, they obtain a payment utility $v > 0$, and also obtain a strictly positive loan surplus. Therefore, in equilibrium, there cannot be any cash users in this case.

Now, a consumer prefers using the bank for payments rather than a FinTech firm if and only if $W_j^B \geq W_j^{FT}$, or $b \geq b_j^c(p)$, where

$$b_j^c(p) \quad = \quad p - \psi(w_j^I - w_j^U). \tag{50}$$

The statement of part (ii) now follows. ■

B.5 Proof of Lemma 2

Let $z \in \{0, v\}$, where $z = v$ represents the case in which the non-bank alternative is cash, and $z = 0$ the case in which the non-bank alternative is a FinTech firm, and let P be the price of the bank's payment services. The bank is uninformed about a fraction $F_h(p - z - \psi\Delta_h^w)$ of high credit type consumers and a fraction $F_\ell(p - z)$ of low credit type consumers, and is informed about (i.e., has payment data for) a fraction $1 - F_h(p - z - \psi\Delta_h^w)$ of high credit type consumers and a fraction $1 - F_\ell(p - z)$ of low credit type consumers. When the bank analyzes payment data, with probability $\frac{\alpha}{1+\alpha}$, it obtains a correct signal about the customer, and with probability $\frac{1}{1+\alpha}$ it obtains an incorrect signal.

Now, let x represent an arbitrary value of Δ_h^w. Then, $\phi(x) = w_h^I - w_h^U$, which can be written as

$$\phi(x) = \left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{\lambda}{2}(\theta_\ell A - 1)^2) \left\{ \frac{\alpha/(1+\alpha)}{\left[\gamma + \lambda(1-\theta_\ell) + \lambda\left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{m_h}{m_\ell}\frac{1-F_h(p-z-\psi x)}{1-F_\ell(p-z)}\alpha\right]^2} \right. + \frac{1/(1+\alpha)}{\left[\gamma + \lambda(1-\theta_\ell) + \lambda\left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{m_h}{m_\ell}\frac{1-F_h(p-z-\psi x)}{1-F_\ell(p-z)}\frac{1}{\alpha}\right]^2} \left. - \frac{1}{\left[\gamma + \lambda(1-\theta_\ell)\lambda\left(\frac{\theta_h}{\theta_\ell} - 1\right)\frac{m_h}{m_\ell}\frac{F_h(p-z-\psi x)}{F_\ell(p-z)}\right]^2} \right\} \tag{51}$$

The left-hand side of the previous equation increases in x. Further, $F_h(p - z - \psi x)$ decreases in x, so that $1 - F(p - z - x)$ increases in x. Hence, overall, the right-hand side decreases in x. Therefore for any p and $z \in \{0, v\}$, there is a unique value of x that solves the equation $\phi(x) = x$; i.e., the mapping $x \mapsto \phi(x)$ has a unique fixed point. ■

B.6 Proof of Proposition 3

We first show that the proposition holds when $\psi = 0$, and then extend the proof to strictly positive but small ψ.

Step 1: The proposition holds for $\psi = 0$.

Suppose first that $\psi = 0$. Then, it follows that $b_h^m = b_\ell^m = p^m - v$, and $b_h^c = b_\ell^c = p^c$. Noting that the distribution of bank affinity F is the same for both credit types, the bank's total profit under payment monopoly is

$$\Pi^m = (1 - F(p - v))p, \tag{52}$$

where we use the fact that $m_h + m_\ell = 1$. The first-order condition is

$$1 - F(p^m - v) - f(p^m - v)p^m = 0 \Longrightarrow p^m = \frac{1 - F(p^m - v)}{f(p^m - v)}. \tag{53}$$

Likewise, under FinTech competition, the bank's first-order condition reduces to

$$1 - F(p^c) - f(p^c)p^c = 0 \Longrightarrow p^c = \frac{1 - F(p^c)}{f(p^c)}. \tag{54}$$

Now, suppose the distribution F has an increasing hazard rate throughout. Then, $\frac{f}{1-F}$ is increasing, or $\frac{1-F}{f}$ is decreasing. Then, because $v > 0$,

$$p^m = \frac{1 - F(p^m - v)}{f(p^m - v)} > \frac{1 - F(p^m)}{f(p^m)} \Longrightarrow 1 - F(p^m) - f(p^m)p^m < 0. \tag{55}$$

Now, observe that the second-order condition in the FinTech competition case is that $1 - F(p) - f(p)p$ decreases in p. Thus, combining $1 - F(p^m) - f(p^m)p^m < 0$ and $1 - F(p^c) - f(p^c)p^c = 0$, we know $p^m > p^c$.

Next, suppose the distribution F has a decreasing hazard rate. Then, $\frac{f}{1-F}$ is decreasing, or $\frac{1-F}{f}$ is increasing. Then, because $v > 0$,

$$p^m = \frac{1 - F(p^m - v)}{f(p^m - v)} < \frac{1 - F(p^m)}{f(p^m)} \Longrightarrow 1 - F(p^m) - f(p^m)p^m > 0. \tag{56}$$

Again, the second-order condition in the FinTech competition case is that $1 - F(p) - f(p)p$ decreases in p. Thus, combining $1 - F(p^m) - f(p^m)p^m > 0$ and $1 - F(p^c) - f(p^c)p^c = 0$, we know $p^m < p^c$.

Step 2: The proposition holds for small but strictly positive ψ.

The bank's profit function when it is a monopolist in payment services is

$$\Pi^m = \sum_{j=h,\ell} m_j \Big[(1 - F(p - v - \psi\Delta_j^w))(p + \psi\pi_j^I) + F(p - v - \psi\Delta_j^w)\psi\pi_j^U\Big]. \tag{57}$$

Denoting $x_j = \pi_j^I - F(p - v - \psi\Delta_j^w)(\pi_j^I - \pi_j^U)$, we can write the bank profit as

$$\pi^m = \sum_{j=h,\ell} m_j \Big[(1 - F(p - v - \psi\Delta_j^w))p + \psi x_j\Big]. \tag{58}$$

We show that the bank's optimal price must lie within an interval $[\underline{p}, \bar{p}]$. First consider the upper bound. When $\psi = 0$, the profit function reduces to $(1 - F(p - v))p = (1 - F(p - v))(p - v) - (1 - F(p - v))v$. Now, as $p \to \infty$, $F(p - v)$ converges to 1 as $p \to \infty$, and by assumption, $(1 - F(p))p$ converges to zero. Thus, $(1 - F(p - v))p$ converges to zero as $p \to \infty$, so that the optimal price when $\psi = 0$ must be finite.

Let S_j^f denote the first-best loan surplus for type θ_j. Then, $x_j = \pi_j^I - F(p - v - \psi\Delta_j^w)\Delta_j^\pi = F(p - v - \psi\Delta_j^w)\pi_j^U + (1 - F(p - v - \psi\Delta_j^w)\pi_j^I > 0$, and π_j^U, π_j^I, and Δ_j^w are each bounded above by S_j^f. Now, by the continuity of Π^m in ψ, we can find some $\psi_0 > 0$ and some $\overline{p} > 0$, such that for any $\psi < \psi_0$, charging any price $p > \overline{p}$ is not optimal for the bank. This is easily seen by observing that $\Pi^m > m_\ell \max_p[(1 - F(p - v))p]$, where $1 - F(p - v)$ is the demand from the low credit type for payment services at price (recall that $\Delta_\ell^w = 0$).

It is equally easy to see that the bank's optimal price has a lower bound. One possible lower bound is $-\psi S_h^f$, i.e., if in the payment market the bank reimburses the full surplus of the loan to the high credit type consumer, the bank would make a loss. We denote such the lower bound by $\underline{p}$.

Now, recalling that Δ_h^w depends on p, the first-order condition when the bank is a monopolist in payment services is

$$0 = \sum_j m_j \left[1 - F(p^m - v - \psi \Delta_j^w) - f(p - v - \psi \Delta_j^w)(1 - \psi \frac{d\Delta_j^w}{dp})p^m + \psi \frac{dx_j}{dp}. \right] \tag{59}$$

By the intermediate value theorem, we can write $F(p^m - v - \psi\Delta_h^w) = F(p^m - v) - \psi\Delta_h^w f(p^m - v - z_1\psi\Delta_h^w)$, where z_1 is between 0 and 1. We can also write $f(p^m - v - \psi\Delta_h^w) = f(p^m - v) - \psi\Delta_h^w f'(p^m - v - z_2\psi\Delta_j^w)$, where z_2 is between 0 and 1. The first-order condition can then be rewritten as

$$\begin{aligned} 0 = 1 - F(p^m - v) - f(p^m - v)p^m + \psi m_\ell \frac{dy_\ell}{dp} + \psi m_h \Big[\Delta_h^w f(p^m - v - z_1\psi\Delta_h^w) \\ + \Delta_h^w f'(p^m - v - z_2\psi\Delta_h^w)(1 - \psi\frac{d\Delta_h^w}{dp})p^m - \frac{d\Delta_h^w}{dp} f(p^m - v)p^m + \frac{dy_h}{dp} \Big] \\ \equiv 1 - F(p^m - v) - f(p^m - v)p^m + \psi x^m, \end{aligned} \tag{60}$$

where $x^m = m_\ell \frac{dy_\ell}{dp} + m_h \Big[\Delta_h^w f(p^m - v - z_1\psi\Delta_h^w) + \Delta_h^w f'(p^m - v - z_2\psi\Delta_h^w)(1 - \psi\frac{d\Delta_h^w}{dp})p^m - \frac{d\Delta_h^w}{dp} f(p^m - v)p^m + \frac{dy_h}{dp} \Big]$. Because the relevant price p^m is in a closed interval $[\underline{p}, \overline{p}]$ and all functions are sufficiently smooth, we can find a uniform upper bound $M > 0$ for $|x^m|$. Then, $1 - F(p^m - v) - f(p^m - v)p^m \in [-\psi M, \psi M]$.

If the hazard rate $f/(1-F)$ is strictly increasing, $(1-F)/f$ is strictly decreasing. In the closed interval $p \in [\underline{p}, \overline{p}]$, the derivative of $(1-F)/f$ is negative and has a lower bound, say $-c$, where $c > 0$ is a constant. The first-order condition of the monopolist bank implies that there exists a $z_3 \in [-1, 1]$ such that

$$\begin{aligned} p^m = \frac{1 - F(p^m - v)}{f(p^m - v)} + z_3 \frac{\psi M}{f(p^m - v)} > \frac{1 - F(p^m)}{f(p^m)} + cv + z_3 \frac{\psi M}{f(p^m - v)} \\ \Longrightarrow 1 - F(p^m) - f(p^m)p^m < -cvf(p^m) - z_3 \frac{\psi M f(p^m)}{f(p^m - v)}. \end{aligned} \tag{61}$$

In similar fashion, we can write the first-order condition of the bank under FinTech competition as

$$0 = 1 - F(p^c) - f(p^c)p^c + \psi x^c, \tag{62}$$

where the right-hand side is strictly decreasing in p, and x^c is a collection of terms analogous to x^m. By an analogous argument that uses continuity, including establishing a closed interval in which the relevant price resides in the competition case, we can find a constant $C > 0$ such that $1 - F(p^c) - f(p^c)p^c \in [-\psi C, \psi C]$, and $1 - F(p) - f(p)p$ is decreasing in p over this interval.

Now, combining the conditions on p^m and p^c, we can choose a sufficiently small ψ so that $1 - F(p^m) - f(p^m)p^m < 1 - F(p^c) - f(p^c)p^c$. Then, given that $1 - F(p) - f(p)p$ is decreasing in p, we have $p^m > p^c$.

The case for a strictly decreasing hazard rate is analogous. ∎

B.7 Proof of Proposition 4

(i) Let p denote the price of the bank's payment services, and let z denote the incremental difference to consumer utility between the bank's payment services and the next best alternative. Then, $z = v$ when the bank is a monopolist in payments, and $z = 0$ when there is FinTech competition.

Let $\Delta_h^w(p, z)$ denote the solution to equation (51). Then, it follows by inspection of equation (51) that $\Delta_h^w(p^c + v, v) = \Delta_h^w(p^c, 0)$. That is, for any given price p^c under competition, if the monopolist bank charges the price $p^c + v$, the resulting value of Δ_h^w remains unchanged. Hence, $b_h^m(p^c + v) = p^c - \psi\Delta_w^h = b_h^m(p^c)$, and $b_\ell^m(p^c + v) = p^c = b_\ell^c(p^c)$. That is, under monopoly, the threshold consumer of each credit type remains the same as in the competition case if $p^m = p^c + v$. As a result, the loan contracts offered in the three cases of uninformed bank, informed bank with high signal, and informed bank with low signal all remain the same as well, so that the profit from the loan market is unchanged.

Let R denote the bank's profit from the loan market. Then, the bank's overall profit under competition is

$$\Pi^c(p^c) = R + \sum_{j=h,\ell} p^c(1 - F(b_j^c(p^c))). \tag{63}$$

Suppose the monopoly bank charges $p^m = p^c + v$. As argued above, the bank's profit from the loan market is unchanged. Therefore, its overall profit is

$$\Pi^m(p^c + v) = R + \sum_{j=h,\ell} (p^c + v)(1 - F(b_j^m(p^c + v))). \tag{64}$$

But as argued above, $b_j^m(p^c + v) = b_j^c(p^c)$ for each $j = h, \ell$. It therefore follows that whenever $v > 0$ and at least one of $F_h^c(b_h^c)$ or $F_\ell^c(b_\ell^c)$ is strictly less than 1, we have $\Pi^m(p^c + v) > \Pi^c(p^c)$.

To complete the argument, note that if p^m is the optimal price under monopoly, it must be that $\Pi^m(p^m) \geq \Pi^m(p^c + v)$, so it follows that $\Pi^m(p^m) > \Pi^c(p^c)$.

(ii) This part follows immediately from noting that the menu of loan contracts offered by the bank always has $q_h = q_h^f$, the first-best quantity for the high credit type, and that in equilibrium the high credit type accepts the contract designed for it.

(iii) Observe that a low credit type earns zero surplus from a loan, regardless of the bank's information or of their bank affinity. Therefore, the change in welfare for this type is determined solely by the surplus they obtain from payments. (a) Consider a low credit type consumer with $b < \min\{b^c(p^c), b^m(p^m)\}$. When the bank is a payment monpolist, this consumer is unbanked, and their overall utility is zero. When there is FinTech competition, this consumer earns the utility from electronic payment services $v > 0$, and their overall utility is v as well. Thus, they are strictly better off with FinTech competition.

(b) Consider a low credit type consumer with $b > \max\{b^c(p^c), b^m(p^m)\}$. This consumer uses the bank to process payments both when the bank is a monopolist and under FinTech competition. Thus the overall utility of this consumer is $b + v - p^m$ under monopoly and $b + v - p^c$ under competition. It follows that they are strictly better off under FinTech competition if $p^c < p^m$, and strictly worse off if $p^c > p^m$. ∎

B.8 Proof of Proposition 5

(i) As shown in equation (11) in Proposition 2, the expected utility of the high credit type from a loan is equal to $w_h^I = \left(\frac{\theta_h}{\theta_\ell} - 1\right) \frac{\lambda}{2} E_s[q_\ell(\kappa(s))^2 \mid \theta_h]$. Let ρ be the intermediate likelihood ratio before the payment signal is obtained. Then, we can write

$$w_h^I(\rho, \alpha) \quad = \quad \left(\frac{\theta_h}{\theta_\ell} - 1\right) \frac{\lambda}{2} \Big\{ \frac{\alpha}{1+\alpha} (q_\ell(\rho\alpha))^2 + \frac{1}{1+\alpha} (q_\ell(\rho/\alpha))^2 \Big\}. \tag{65}$$

From Proposition 1 part (i), $q_\ell(\kappa) = \frac{\theta_\ell A - 1}{\gamma + \lambda(1-\theta_\ell) + \lambda\kappa\left(\frac{\theta_h}{\theta_\ell} - 1\right)}$ is strictly decreasing in κ. Hence, it follows that $q_\ell(\rho\alpha)$ and $q_\ell(\rho/\alpha)$ are each strictly decreasing in ρ, so that $w_h^I(\rho, \alpha)$ is strictly decreasing in ρ.

As the low credit type obtains zero surplus in all cases, we have $w_\ell^I(\rho, \alpha) = 0$. Therefore, $b_\ell^s(p) = p + \psi y$.

Now, suppose that $b_h^s(p) < b_\ell^s(p) = p + \psi y$. Then, as the bank affinity distribution is the same for both types, it follows that $1 - F(b_h^s(p)) > 1 - F(b_\ell^s(p))$ and $F(b_h^s(p)) < F(b_\ell^s(p))$, so that $\rho^B = \frac{1-F(b_h^s(p))}{1-F(b_\ell^s(p))} \frac{m_h}{m_\ell} > \rho^{FT} = \frac{F(b_h^s(p))}{F(b_\ell^s(p))} \frac{m_h}{m_\ell}$. But $w_h^I(\rho, \alpha)$ is strictly decreasing in ρ, so it follows that $w_h^I(\rho^B, \alpha) < w_h^I(\rho^{FT}, \alpha)$, so that $b_h^s = p + \psi y + (w_h^I(\rho^{FT}, \alpha) - w_h^I(\rho^B, \alpha)) > b_\ell^s = p + \psi y$, which is a contradiction.

A similar argument rules out the case that $b_h^s(p) > b_\ell^s(p)$, leaving only the possibility that $b_h^s(p) = b_\ell^s(p)$.

(ii) This part follows immediately from part (i) on noting that $\rho^B = \frac{1-F(b_h^s(p))}{1-F(b_\ell^s(p))} \frac{m_h}{m_\ell}$ and $\rho^{FT} = \frac{F(b_h^s(p))}{F(b_\ell^s(p))} \frac{m_h}{m_\ell}$. ∎

B.9 Proof of Proposition 6

(i) Consider the equilibrium under data portability in which all consumers port their data to the bank for free. As discussed in the text, this case is equivalent to data sales by the FinTech firm at a price of zero. The proof of Proposition 5 applies for all values of the price of data under data sales, including $y > 0$ and zero. Hence, it follows that the loan market outcomes are identical between data sales and data portability.

(ii) Consider the data sales regime, and suppose the bank pays a price y to the FinTech firms for acquiring payment data of FinTech customers. Write the bank's expected profit from a loan to credit type θ_j when it is informed as $\pi_j^I(\rho, \alpha)$, where ρ is the intermediate likelihood ratio before the payment signal. Under the same affinity distribution between the two credit types, we have $b_h^s = b_\ell^s = p + \psi y$, and $\rho^B = \rho^{FT} = m_h/m_\ell$.

Then, the bank's overall profit is simplified as

$$\Pi = \sum_j m_j \left[(1 - F(p + \psi y))p + \psi(1 - F(p + \psi y))\pi_j^I(\frac{m_h}{m_\ell}, \alpha) + \psi F(p + \psi y)(\pi_j^I(\frac{m_h}{m_\ell}, \alpha) - y) \right]. \tag{66}$$

The first-order condition for the optimal price is

$$0 = \sum_j m_j \left[-f(p + \psi y)(p + \psi y) + 1 - F(p + \psi y) \right]. \tag{67}$$

Observe that this equation is of the form

$$0 = \sum_j m_j \left[-f(x)x + 1 - F(x) \right], \tag{68}$$

where $x = p + \psi y$.

Denote $G(x) = -f(x)x + 1 - F(x)$. Then, by the implicit function theorem,

$$\frac{dp}{dy} = -\frac{G'(x)\frac{\partial x}{\partial y}}{G'(x)\frac{\partial x}{\partial p}} = -\psi < 0. \tag{69}$$

That is, the bank's price for payment services increases as y decreases. Hence, comparing data sales (with a data price of $\hat{y} > 0$ and data portability (with a data price of zero), the bank's price for payment services is strictly greater under data portability.

The FinTech firms charge a price for payment services $-\psi\hat{y}$ under data sales, and a price zero under data portability. Hence, all consumers are paying strictly more for payment services under data portability, whereas the loan market outcomes are identical in both the data sales and data portability regimes. It follows that all consumers strictly prefer data sales to data portability. ∎

C Example on the Effects of FinTech Competition

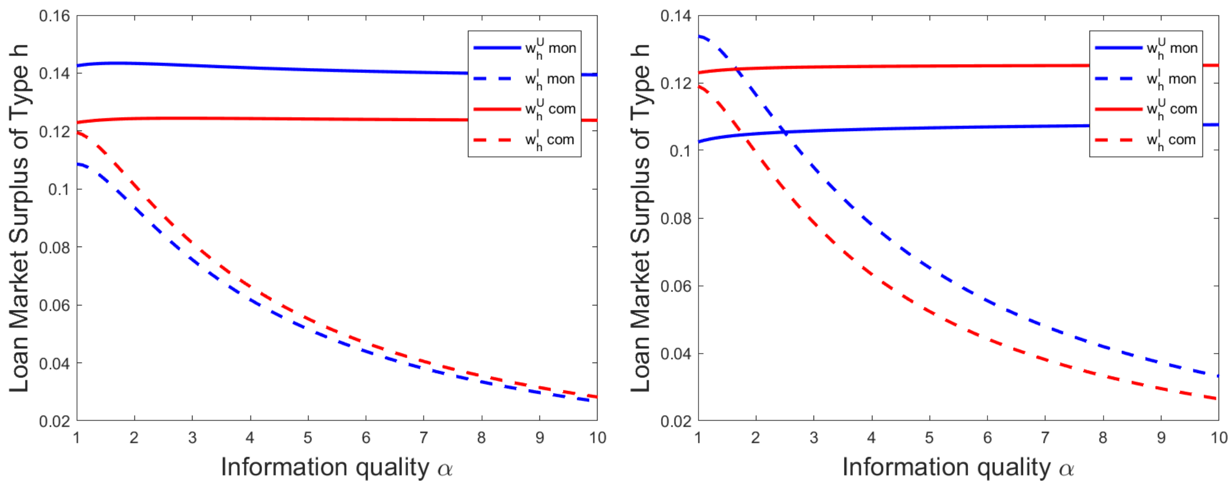
We set $A = 2, \theta_h = 0.99, \theta_\ell = 0.8, \lambda = 0.4, \gamma = 0.2, \psi = 1, \alpha = 2$, and $m_h = 5 = m_\ell = 0.5$. Figure 5 shows the equilibrium loan surplus captured by credit type θ_h as a function of α, the precision of the signal extracted from payments. Figure 6 shows the total surplus from a loan to the low credit type in equilibrium, as α varies.[18] In each figure, the bank affinity distribution for the low credit type, F_ℓ, is set to be exponential with mean 1. The bank affinity distribution for the high credit type, F_h is Weibull with first parameter $k = 2$ (implying an increasing hazard rate) in Figure (a) and $k = 0.5$ (implying a decreasing hazard rate) in Figure (b). The second parameter of the Weibull distribution is set to 1.

For each set of parameter values and payment market structure, we first compute the optimal price of bank payment services. The numerical computation involves using Lemma 2 to pin down a fixed point in Δ_h^w for each p. The bank's profit function can then be computed,

[18] Recall that the bank captures the entire loan surplus from a loan to the low credit type.

and the optimal price determined. The relative masses of consumers using the bank (and not using the bank) at the optimal price determine the optimal menu of contracts in each case.

Bank payment customers obtain a menu based on the signal they have generated. Recall that high credit types generate a high signal with probability $\frac{\alpha}{1+\alpha}$ and a low signal with probability $\frac{1}{1+\alpha}$, with the probabilities being reversed for low credit types. When the bank is informed, the expected loan surplus captured by a high credit type and the total surplus from a loan to the low credit type take these probabilities into account.



(a) F_h has increasing hazard rate (b) F_h has decreasing hazard rate

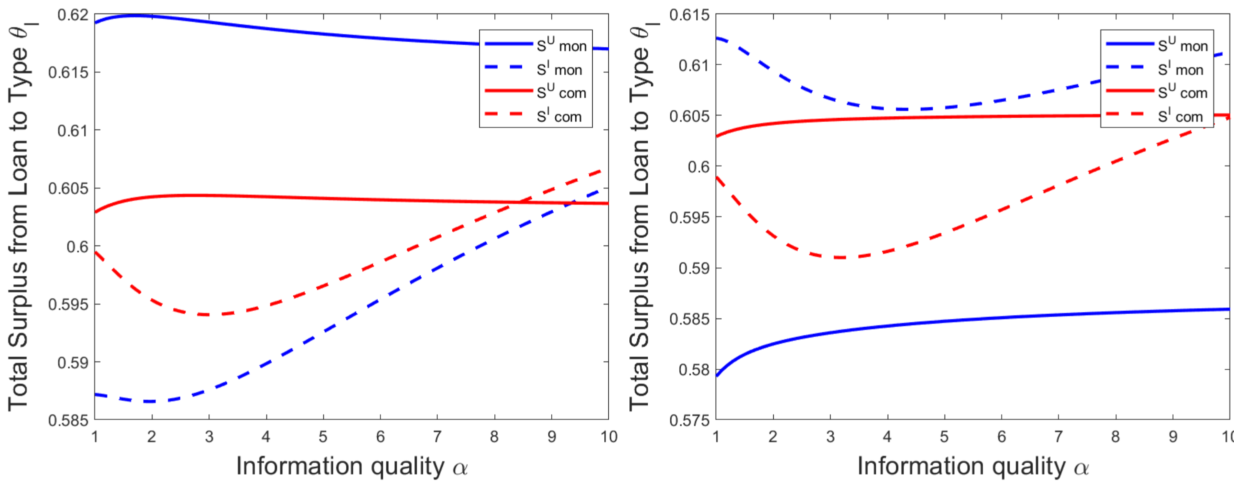
Figure 5: **Expected Loan Surplus Captured by Credit Type θ_h**
This figure plots the expected loan surplus captured by credit type θ_h for different parameter values and payment market structures. Here, $A = 2, \theta_h = 0.99, \theta_\ell = 0.8, \lambda = 0.4, \gamma = 0.2, \psi = 1, \alpha = 2, m_h = 5, m_\ell = 0.5$. The bank affinity distribution for credit type θ_ℓ is exponential with parameter 1. In figure (a), the bank affinity distribution for credit type θ_h is Weibull with first parameter $k = 2$. In figure (b), the bank affinity distribution for credit type θ_h is Weibull with first parameter $k = 0.5$. The second parameter of the Weibull is set to 1 in both cases. For each set of parameters, we find the optimal price for bank payment services. The blue lines indicate the bank is a monopolist in payment services, and the red lines that the bank faces FinTech competition. The solid lines indicate the bank is uninformed about the consumer, and the dashed lines that the bank is informed.

Consider Figure 5 (a), and start with the case in which the bank is a monopoly provider of payment services. Here, the bank affinity distribution for the low credit type is exponential, and the bank affinity distribution for the high credit type has an increasing hazard rate. Given the parameters, at any price, the pool of consumers who use the bank for payment services includes a larger proportion of high credit types than the prior probability of 0.5. Conversely, the pool of consumers who are not bank payment customers includes fewer high credit types than the prior. Therefore, the bank extracts a higher rent from payment customers who have the high credit type. As a result, the latter have a lower utility from the loan. Conversely, high credit types who do not use the bank for payment services benefit.

Now, consider the effects of FinTech competition. Relative to the bank monopoly case, FinTech competition skews the pool of bank payment customers a little more toward the low credit type. Thus, when the bank is uninformed, the high-credit type obtains less favorable terms and has an even lower utility from the loan. That is, high credit types who are payment non-customers are worse off after FinTech entry. As a result, high-credit types who remain bank payment customers obtain a lower surplus from the loan after FinTech competition.

Figure 5 (b) embodies similar reasoning. Here, the bank affinity distribution of high credit types has an increasing hazard rate. FinTech competition skews the pool of bank payment customers toward the high credit type, so that the high credit type obtains less favorable terms (compared to the bank monopoly case) when the bank is informed. Therefore, bank payment customers are worse off in the loan market under FinTech competition. Conversely, among high credit types, bank payment non-customers obtain a higher surplus from the loan under FinTech competition.

Figure 6 shows the total surplus from a loan to the low credit type. Recall that this loan surplus is entirely captured by the bank. From Proposition 2, both the total surplus from a loan to the low credit type and the amount of loan surplus captured by the high credit type depend on the quantity offered to the low credit type. Thus, it is not surprising that the effect of FinTech competition on the total surplus from the low credit type is similar to its



(a) F_h has increasing hazard rate (b) F_h has decreasing hazard rate

Figure 6: **Expected Total Surplus from Loan to Credit Type θ_ℓ**
This figure plots the expected total surplus (i.e., the sum of bank profit and consumer surplus) from a loan to credit type θ_ℓ for different parameter values and payment market structures. Here, $A = 2, \theta_h = 0.99, \theta_\ell = 0.8, \lambda = 0.4, \gamma = 0.2, \psi = 1, \alpha = 2, m_h = 0.95, m_\ell = 0.05$. The bank affinity distribution for credit type θ_ℓ is exponential. In figure (a), the bank affinity distribution for credit type θ_h is Weibull with first parameter $k = 2$. In figure (b), the bank affinity distribution for credit type θ_h is Weibull with first parameter $k = 0.5$. For each set of parameters, we find the optimal price for bank payment services. The blue lines indicate the bank is a monopolist in payment services, and the red lines that the bank faces FinTech competition. The solid lines indicate the bank is uninformed about the consumer, and the dashed lines that the bank is informed.

effect in Figure 5. Keeping all else fixed, when F_h has an increasing hazard rate, FinTech competition improves this surplus among bank payment customers, and reduces it among non-customers. The converse effects occur when F_h has a decreasing hazard rate.

More surprisingly, the expected surplus from a loan to the low credit type payment customer is non-monotone in α, the precision of the signal extracted from payments. When α is high, the low credit type is unlikely to generate a high signal. The high precision of the low signal allows the bank to set the loan quantity for the low type close to its first-best level. Therefore, for high α, the surplus from a loan to the low-credit type must be increasing in α. For values of α close to 1, the additional information from payments allows the bank to vary q_ℓ with the signal in a non-linear way. As the low credit type still generates the high signal with sufficiently large probability for such values of α, the overall expected surplus falls given our parameter values.

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