BIS Working Papers

No 1037

Big Techs vs Banks

by Leonardo Gambacorta, Fahad Khalil and
Bruno M Parigi

Monetary and Economic Department

August 2022

JEL classification: E51, G23, O31.

Keywords: Big techs, credit markets, privacy,
information sharing

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Big Techs vs Banks*

Leonardo Gambacorta, BIS, Switzerland   Fahad Khalil, Univ. of Washington, USA
Bruno M. Parigi, Univ. of Padova, Italy

Abstract

We study an economy in which large technology companies, big techs, provide credit to firms operating on their platforms. We focus on two advantages that big techs have with respect to banks: better information on their clients and better enforcement of credit repayment since big techs can exclude a defaulting firm from their ecosystem. While big techs have both superior enforcement and complete and private information of the firm type big techs can encroach on banks' turf only if they guarantee some *privacy* to firms by tempering their drive to collect information about firm characteristics and leaving some rents to them. The way big techs share information i.e. by providing information publicly or in a private way entails different outcomes in terms of efficiency.

JEL Classification: E51, G23, O31.

Keywords: Big techs, credit markets, privacy, information sharing

---

*We thank an anonymous referee for very useful comments. We also thank Leonardo Madio, Han Qiu, the audiences at the University of Padova, the 2020 CefES Conference on European Studies, the Hong Kong Institute for Monetary and Financial Research, and the BIS for useful comments and suggestions. Bruno Maria Parigi gratefully acknowledges financial support from Hong Kong Institute for Monetary and Financial Research. This paper represents the views of the authors, which are not necessarily the views of the Hong Kong Monetary Authority, Hong Kong Institute for Monetary and Financial Research, or its Board of Directors or Council of Advisers, or those of the Bank for International Settlements. The above-mentioned entities except the authors take no responsibility for any inaccuracies or omissions contained in the paper. Corresponding author: Bruno Maria Parigi, University of Padova (email: brunomaria.parigi@unipd.it).

1 Introduction

In the last decade large technology companies, also known as big techs, have moved into the provision of financial services.[1] Big techs have become substantial players in payments in several advanced and emerging market economies (BIS, 2019). For example, big techs have come to account for 94% of mobile payments in China in the space of just a few years (Carstens et al, 2021). Big tech credit grew by 40% in 2020 alone, to a global total of over US$700 billion. In some jurisdictions big techs participated in government credit schemes during the Covid-19 pandemic period (Cornelli et al, 2021).[2] Recently big techs have started competing with banks especially in the market for loans to small and medium sized enterprises (SMEs). This paper is about the competition between big techs and banks in the loan market for SMEs where adverse selection and difficulty of enforcing repayment cause frictions. In this paper we will focus on loans to firms, in particular SMEs, because big techs mainly provide credit to small vendors in their ecosystem.[3]

Big techs have access to massive amounts of data about firms that sell through their online platforms or use their QR-code payment systems. These data are rarely acquired from the firm directly, rather they are extrapolated from observing of the behaviour of

[1] Big techs are major digital players such as Google, Amazon, Facebook, Apple and Microsoft in Europe and United States, and Baidu, Alibaba, Tencent and Xiaomi in Asia. Some also venture into offering financial services (e.g. Alibaba, Tencent). Big techs have a range of business lines, of which lending represents only one (often small) part, while their core business activity is typically of a non-financial nature. By contrast, fintechs are financial companies that focus their business models around decentralised platforms where individual lenders choose borrowers or projects to lend to in a market framework (e.g. P2P lending as in LendingClub).

[2] The data show that globally, big tech credit is booming, overtaking fintech credit (Cornelli et al, 2019). The largest markets for big tech credit in absolute terms are China, Japan, Korea and the United States. China is the biggest market with big tech giants such as Ant Group operating also in the provision of wealth management and insurance products. In Japan, e-commerce firm Rakuten and social media company LINE are notable lenders. big tech credit is more developed when banking services are more expensive (higher banking sector mark-ups) and also where there is a larger un(der)met demand for financial services, as proxied by fewer bank branches per capita (Cornelli et al, 2020).

[3] As examples of big techs providing credit to small vendors in their online platforms see Alibaba's Taobao platform in China or Mercado Pago for Mercado Libre in Mexico. We ignore loans to large companies (not developed so far) and to households (granted mainly in the form of consumer credit). Although we do not target a specific institutional environment, our work is related mainly to Asia, Africa and Latin America, as regulation has somewhat limited the financial footprint of the big techs in Europe.

entrepreneurs and consumers (Argenziano and Bonatti, 2021). While this information is valuable in improving the assessment of a firm's credit risk, it can also be exploited by the lender as we know from the relationship banking literature (e.g. Sharpe, 1990). In the case of big tech lending, this problem is compounded by the fact that firms are somewhat captive in the big tech ecosystem. In fact, a default on a big tech loan may lead not only to the exclusion of the firm from future loans as in the case of bank lending but also to the exclusion from the ecommerce platform (and thus from future sales) or from use of the payment system run by the same big tech. We show how competition between banks and big techs in attracting borrowers can lead to greater *privacy* of borrowers as Big techs have an incentive to temper their drive to collect information about firm characteristics. In other words, to earn the loyalty of their client firms, big techs have to self-limit their capacity to extract rents. At the same time greater privacy has a cost. The limited capacity of big techs to recognize the firm's type increases the number of inefficient defaults and reduces investment in profitable opportunities. One way to mitigate these inefficiencies is for big techs to share their data with the banks that make loans funded with cheap deposits.

As Frost et al (2019) argue, big techs present a distinctive business model due to the combination of: (i) network effects, generated by ecommerce, messaging applications, search engines, payment services, etc., and (ii) technology, e.g. artificial intelligence using big data and machine learning. Network effects and technology lead to superior enforcement and superior information that differentiate big tech lending from bank lending and will constitute two building blocks of our model.

First, big techs offering loans to firms that sell products on their online platforms (or use their payment apps) have an advantage over banks in enforcing loans repayments and preventing voluntary defaults. The threat of exclusion — or even of a reputational downgrade within a "captive" ecosystem — after a default provides big techs with an extra-legal but powerful contract enforcement tool.[4]

Second, big techs gain additional information about the firms from the huge amount of data that they collect on the platform (sales, product quality reviews, reputation with clients) something that the banks cannot observe. While a bank would learn imperfectly through a firm's history of repayments, among other information, its probability of being able to repay the loan, a big tech would learn this probability much faster and much

[4]Superior debt enforcement need not bring efficiency improvements if as Fong et al (2021) argue it leads to costly liquidation of assets.

more accurately and with no human intervention.[5] This information enables big techs to screen clients more effectively than banks.

We have in mind an environment with limited enforcement of loan repayment.[6] Model-wise, this implies a scope for *strategic default*, in the spirit of Bolton and Scharfstein (1990), i.e., a firm may choose to default even when it has enough cash on hand to repay a loan. Strategic defaults by solvent firms are a key measure of inefficiency as such firms could profitably self-finance their investment if not for the fact that they require external funding. This option to default strategically translates into an incentive compatibility constraint on the repayment a lender can ask such that a firm's continuation value after repayment should not be smaller than its post default alternative. These two features lead to the result (Lemma 1) that, in an environment with limited enforcement of loan repayment, a more powerful retaliation after default increases welfare as it reduces strategic defaults by solvent firms. In this respect, big tech lending is more efficient since the post-default alternative on a big tech loan is worse than on a bank loan because of the additional penalty of exclusion from the big tech ecosystem.

We focus on the trade-off between data privacy and efficiency. Data privacy refers to the information that big techs learn about borrowers, and what they do with it, including sharing it with other agents. Given the detailed information the big tech has about firms which trade on the platform and become its clients, there is a concern that the big tech can take advantage of its captive user base. In particular, there is the concern that the big tech can jack up the price of its financial services to extract a larger share of their surplus. We assume that a big tech learns the type of a firm precisely,

[5] Big data obtained directly from big tech platforms typically include: i) transactions (sales volumes and average selling prices); ii) reputation (claim ratio, handling time and complaints); and iii) industry-specific characteristics (sales seasonality, trend and macroeconomic sensitivity). See Hau et al (2018) and Frost et al (2019) for more details.

The big tech will know if the retailer or manufacturer enjoys low or high product return margins and be able to infer from customer reviews the quality of products or service supplied (Zetzsche et al, 2017). As Frost et al (2019) argue, due to their extensive use of artificial intelligence, big techs may be able to better organise and process the data, relative to banks. The superiority of big techs in organising the data from different sources allow them to construct comprehensive databases to assess customers' preferences and behaviours. Big data can then be processed through machine learning algorithms that establish correlations between client-specific characteristics/preferences and creditworthiness, so as to provide a much more precise assessment of credit-worthiness than traditional banks do.

[6] For example, it could be that collateral is not available, and/or the efficiency of the judicial system is low, and/or there are prohibitive costs to enforce repayments, and/or the loan size is too small to make the fixed cost of enforcement worthwhile.

while a bank will only know the distribution of types. Thus, a big tech can charge a type-specific repayment, while a bank can only charge one fixed payment from any firm that borrows from it. A big tech cannot stop itself from using its information and demanding the maximum repayment that a firm can afford. This introduces a principal incentive compatibility constraint (PIC) on a big tech based on the information that it receives from data processing. An interesting aspect of this constraint is that a big tech internalizes the possibility of strategic defaults by solvent firms more precisely than a bank. As banks have less information about the credit worthiness of a client and the probability of success of its investment, bank-lending can only account for strategic default 'on average'. This results in strategic default by risky solvent firms making bank lending less efficient than big tech lending.

We will focus on a representative bank and a representative big tech that compete in repayment rates subject to the constraint that they break even. In an extension we consider the impact of market power for the big tech. As long as they have the choice to borrow from a bank or a big tech, firms will not borrow from a too powerful big tech that learns a firm's type perfectly and privately. Firms would rather borrow from the bank at a fixed rate (Proposition 1).

The big tech can encroach on banks' turf only if it offers rents to firms by guaranteeing privacy in terms of refraining from collecting information. We envision a mechanism where, before lending, the big tech sets up a technology to collect information that will generate a noisy signal about the firm type. This makes the big tech uncertain about the true firm type and prevents it from charging the maximum that a firm of that type can repay. In Proposition 2, we illustrate how the competition between the bank and the big tech will play out among firms of different risk. In particular, we establish that insolvent firms will borrow from the bank because the big tech excludes them; risky but solvent firms will choose to borrow from the bank at a fixed rate and default given the higher post default payoff from bank lending; the intermediate risk firms will borrow from the big tech at a type contingent rate with a privacy discount and will not strategically default; finally the safest firms will prefer to borrow from the bank at a fixed rate, enjoy a positive profit and will not strategically default.

Our model allows us also to shed some light on how the big techs could be made to share the vast reams of data they have collected on firms. This aspect is important because there is an ongoing debate on the trade-offs and limits of alternative information arrangements between big techs and banks. Options also include the possibility of special separate credit-scoring joint-ventures that would be partly state-owned (Yu and

McMorrow, 2021).

In particular, we investigate two information-sharing arrangements. In one, the big tech makes data public for any bank that wants to use them, e.g., by conferring the firm type information to a public credit bureau. In the other arrangement, the big tech privately gives the firm type information to the bank, e.g., by selling it credit scoring services.

Although, apparently similar, these two ways of sharing information lead to different outcomes. When banks compete for firms, providing public information to banks, they end up rationing solvent firms (if the judicial system is not able to fully avoid strategic defaults), while sharing information privately exploits all gains from trade.

The different outcomes stem from the fact that when information is shared privately the joint venture (big tech-bank) can engage in cross subsidies that are robust to competition as an entrant cannot commit not to charge the maximum repayment since the information learned is private and hence not contractible. By contrast, when the information is shared publicly a potential entrant could engage in a familiar cream-skimming strategy unless there is a regulated scheme that prevents competition from breaking the cross-subsidy.

The remainder of the paper is organised as follows. In Section 2 we review the related literature and in Section 3 we set up the model. In Section 4 we study competition between bank and big tech and show that no firm will borrow from a fully informed big tech that will use information to extract its surplus. In Section 5 we show that to be able to encroach on a bank's turf, the big tech must guarantee some privacy to the firms. In Section 6 we study how the big tech might share information with the bank. Section 7 discusses some extensions and concludes. The proofs are in the Appendix.

2 Related literature

Our paper relates to three main strands of literature. First it relates to the literature on relationship banks (or R-bank for short) and transactional banks (T-bank). The various streams of this literature focus on different and interconnected roles for R-banks and T-banks. Big tech lending has characteristics of both lending types, because the loan offered to the client follows a period of interaction on the platform (similarly to R-bank), but at the same time the cost (for the big tech) of a termination of the relationship with the client is quite limited (T-bank). Our paper based on a learning mechanism is very much related to the stream of the relationship literature that emphasizes (soft) information acquisition about borrowers' types over time (Sharpe, 1990; Rajan, 1992; Von Thadden, 1995; Bolton et al, 2016). This strand of theories puts the R-bank in the position of offering continuation lending terms that are better adapted to the specific circumstances in which the firm may find itself in the future. We also add to the relationship banking literature the dimension of the superior enforcement of loan repayments that follows from the fact that borrowers are somewhat captive in the big tech ecosystem.

Second, our paper is related to the literature on fintech and big tech lending and the use of credit scoring techniques based on machine learning and big data to better assess firms' credit worthiness. Fintech credit is typically based on peer to peer (P2P) platforms that facilitate the direct matching between a borrower and a lender (see Belleflamme et al, 2016 for a review of the literature). This kind of credit is different from big tech credit offered to firms operating on an ecommerce platform or using big tech's payment app. Fintech lenders do not raise funds and do not retain credit risk, their sources of income being only the fees paid by the borrowers and the lenders. However, fintech credit is based on credit scoring models that use machine learning and non-traditional data as in the case of big tech credit. In particular, a few studies have analysed how credit supplied by fintech firms, and their scoring models perform compared with traditional bank lending. Jagtiani and Lemieux (2018) compare loans made by a large fintech lender and similar loans that were originated through traditional banking channels. Specifically, they use account-level data from LendingClub and the Y-14M data reported by bank holding companies with total assets of US$50 billion or more. They find a high correlation between interest rate spreads, LendingClub rating grades (that use non-traditional data) and loan performance.

Several papers have studied competition between traditional banks and big techs that use data from vendors and consumers online trading (Hau et al 2019) or from payment services (Parlour et al 2020) for credit analysis. A common theme is that big tech credit is relatively more attractive for borrowers with low credit scores and with weak bank relationships. This prediction, which is consistent with our results, is supported by the empirical analysis based on credit data from Ant Financial. Ant Financial uses the transaction data on its retail site Taobao (China's largest ecommerce platform) to generate credit scores for the online vendors.

In a spatial model of bank competition Vives and Ye (2021) study how the diffusion of information technology brought about by the entry of fintechs and big techs in credit markets affects competition. Improvements in information technology increase welfare if they weaken the influence of bank–borrower distance on monitoring/screening costs, which happens if banks have local monopolies.

We add to this strand of literature the notion that competition between banks and big techs is not only affected by information but also by the superior enforcement ability of the big tech. We show that the combination of better information and superior enforcement may act as a barrier to entry for big techs, unless they find ways to protect the privacy of the vendors, which leads us to discuss the last strand of literature.

Third, our paper is related to the growing literature of the economics of privacy (see Acquisti et al, 2016 for a survey). This literature studies the economic value and consequences of protecting and disclosing personal information, and the trade-offs between efficiency and privacy. We stress three dimensions that are relevant for our work. First, the rapid advance in information technology makes it feasible for sellers to price discriminate by conditioning their price offers on consumers' prior purchase behaviour. However, as Acquisti and Varian (2005) argue, consumers are far from defenceless and it is likely that sellers will have to offer buyers some benefits to induce them to reveal their identities, to the point that under certain conditions sellers do not want to condition current price offers on past behaviour. A related example is Calzolari and Pavan (2006), who study an upstream seller who might sell information to a downstream seller about the willingness to pay of a common buyer. The upstream seller may prefer to maintain the privacy of the buyer if the extra rent it would have to offer the buyer to disclose information exceeds the profit by selling information to the downstream seller. Second, one theme of the line of research on privacy and price discrimination is that firms often benefit from committing to privacy policies. For example, Taylor (2004) argues that a company's privacy-intrusive strategy is counterproductive. He shows that even in the presence of tracking technologies that allow merchants to engage in price discrimination, regulation may not be necessary. If consumers are aware of how merchants may use their data and adapt their behaviours accordingly, it is in a company's best interest to protect customers' data. In line with this strand of literature our work shows that big techs have an incentive to commit to protect firms' data to compete against banks.[7] However, as He et al (2020) point out the voluntary nature of data sharing which is at the root of open banking may not be sufficient to protect consumer's welfare in credit markets plagued by adverse selection. Welfare could be reduced when the mere sign-up decision signals the credit quality. A third issue is the concern that more stringent

[7] Our work is also linked to the broader issue of strategic ignorance (Carrillo and Mariotti, 2000).

data-protection regulations may lead to reduced access to credit, thus creating a trade off with consumer privacy. Pagano and Jappelli (1993) and Jappelli and Pagano (2002) show that if banks share information about their customers, they would increase lending to safe borrowers, thereby decreasing default rates.

3 Model set up

3.1 Investments

There are three periods: $t = 0, 1, 2$. At $t = 0, 1$ each firm has an investment opportunity of fixed size normalised to 1. Firms have limited wealth, that we assume to be zero, to finance an investment at $t = 0$. This is a typical feature of SMEs, characterized by a limited amount of outside equity invested in the company and no assets to pledge as collateral. For these types of borrowers, the only potential source of funds is a loan, a feature that we will assume in the model. Banks and big techs provide the loans competing in the credit market. As shown above (Cornelli et al, 2019) some big techs have ventured into lending, mainly to SMEs and consumers. Loans offered are typically credit lines, or small loans with short maturity (typically up to one year), rolled over after repayment.

A firm's output per period is $Y > 0$ in case of success, and 0 in case of failure. The opportunity cost of funds for a bank is 0, while big techs which do not have access to deposits, face an opportunity cost of $r \geq 0$. There is no discounting across periods, and all players are risk neutral.

We capture firms' heterogeneity by assuming that their investments have different probabilities of success p, with $p \in [0, 1]$, density function $f(p)$, and cumulative $F(p)$; the type p is known to the firm; the lender only knows $f(p)$. We allow for insolvent firms, i.e. with Net Present Value < 0, or $pY < 1$.

3.2 Repayment Enforcement

We consider an environment with limited repayment enforcement (e.g., Bolton Scharfstein, 1990). While investment is observable, output is not observable to outsiders at any cost.[8] Our setting captures situations in which the judicial system is inefficient, or there are large fixed costs to assess outcomes as in the case of SME lending. Hence, when the output is Y, either a firm repays the loan voluntarily, or defaults, which we call a strategic default. As we will see, a key welfare criterion in the model is the fraction of solvent firms that strategically default.

At $t = 0$, the lender makes a loan of size 1 that specifies a repayment R by the borrower at $t = 1$. After success, if the borrower repays, it is free to self-finance a new investment of 1 to obtain an expected payoff of pY at $t = 2$. If the borrower does not repay, the lender can prevent the borrower from investing again. Thus, we assume that reinvestment is observable and the lender can prevent it if the borrower does not repay in $t = 1$.[9]

Note that, in our setting, it follows immediately that a firm is 'locked-in' in a two-period relationship with the lender and has no outside option at period $t = 1$. This is to capture the key concern that a firm is 'captive' in a big tech ecosystem and is susceptible to being exploited by the big tech's information at the interim stage. Anticipating strategic default, no lender would provide funding to a borrower attempting to switch in the interim stage. While competition between lenders occurs at the stage of the initial loan, each firm takes a loan only from one lender in equilibrium. Thus, competition between lenders determines the loan structure, and we rely on the lock-in feature to capture the popular concern about a big tech exploiting its information advantage in the interim stage.

Strategic default means that in case of success the firm keeps Y and saves on repayment. A firm's value of the retained Y depends on the enforcement ability of the lender. We assume that a big tech has superior enforcement ability with respect to a bank in that a big tech can exclude a defaulting firm from future trades and from access to the payment system, so that a defaulting firm can at most consume Y. By contrast with income Y, a firm defaulting from a bank can conduct trades with net return ρY,

[8] This is a more extreme friction than in the Costly State Verification model (Townsend, 1979) where outsiders can verify the state of nature at a finite cost.

[9] Observe that repaying R and being allowed to self-finance a new investment of size 1 is equivalent to repaying $R + 1$ and receiving a roll over loan of 1. In our finite horizon setting, this would require commitment to lend upon repayment as the borrower would default for sure in the last period. However, while we observe loan roll over after repayment, we do not observe contractual commitments from Big Techs, or banks, to roll over. Thus, in our model, we do not rely on such a commitment assumption. Being able to prevent reinvestment after default provides sufficient incentive to a lender to offer an initial loan.

where $\rho > 1$.

Thus, the parameter ρ measures the (negative of) the enforcement ability of a bank. The parameter ρ can be interpreted as reputation or *collateral* since it captures (the negative of) what a firm loses when it defaults.[10] Note that ρ can also be interpreted as the (negative of the) differential benefit of operating in a big tech ecosystem.[11]

The difference $\rho - 1$ also captures the degree of exclusivity of the agreements between firms and big techs. At one extreme are agreements that force firms to sell through only one platform («choose one from two»). At another extreme a firm is excluded only from ecommerce of a big tech whose loan it defaults. In the Conclusions section we discuss policy issues related to the post default options.

In sum, if a firm repays R, it is allowed to reinvest 1 with its own funds and can expect to earn pY in $t = 2$. If it defaults on a bank loan, it receives ρY in $t = 1$. Thus, under a bank loan, the repayment R must satisfy the following incentive compatibility constraint for a firm of type p upon receiving Y:

$$Y - R - 1 + pY \geq \rho Y. \tag{IC}$$

The LHS is the firm's payoff from repaying R and investing 1 in a new project that will yield pY. The RHS is what the firm can obtain by strategically defaulting at $t = 1$. If a firm defaults on a big tech loan, it receives Y in $t = 1$ and the RHS of its incentive constraint is of course just Y, while the LHS is unchanged.

From (IC), we obtain the important cut-offs for bank and big tech loans, denoted,

[10]This resembles the problem of why a country may not want to default on its sovereign debt. Cole and Kehoe (1995) have studied the case of a country that may not want to default on its sovereign debt to avoid losing trade agreements.

[11]The mere use of big tech products and services could generate some sort of discount effects. In fact it is typical for big tech companies to use information obtained in their ecosystem to offer targeted discounts to their customers, although in general it happens at the expense of their competitors. For example, if clients use credit or other financial products on the payment platform Alipay in China or use a credit line, clients get "points" to be used to receive money and other free products. These benefits would be lost upon exiting the big tech ecosystem. Finally, besides exclusion from e-commerce and payment services the superior enforcement ability of the big techs can also be justified because in some instances they can seize the receivables of these companies in their accounts to repay their debts (Gambacorta et al, 2020).

respectively,[12]

$$\widehat{p}_b = \frac{R+1}{Y} + \rho - 1, \tag{1}$$

$$\widehat{p}_0 = \frac{R+1}{Y}, \tag{2}$$

such that a firm will repay R if and only if p is bigger or equal than its cutoff $\widehat{p}_i$, for $i = b, 0$. Firms with p smaller than their cutoff will default strategically at $t = 1$ and will be prevented from investing again.

To illustrate the welfare impact of enforcement it is convenient to consider a benchmark with a representative lender with $\rho > 1$ and $r \geq 0$ subject to a zero expected profit condition,

$$\mathbb{E}\left(\Pi\right) = \int_{\frac{R+1}{Y}+\rho-1}^{1} pRf\left(p\right)dp - \left(1+r\right)\int_{0}^{1} f\left(p\right)dp = 0, \tag{3}$$

where R denotes the break-even repayment. It is inefficient if R is so high that solvent firms with $p > 1/Y$ strategically default, $\widehat{p} = \frac{R+1}{Y} + \rho - 1$. Thus we will focus on the conditions that induce solvent firms to repay and continue in $t = 1$. The following Lemma establishes that tougher enforcement increases welfare as it reduces the fraction of solvent firms that strategically default, which also implies a lower break-even repayment R.

Lemma 1. In economies where enforcement is tougher (i.e. where ρ is lower) both the break-even repayment R satisfying the zero-expected profit condition (3) and strategic defaults decline

Proof. See Appendix.

This result establishes that, everything else constant, an institutional environment that allows tougher retaliations against defaulters, discourages strategic defaults, lowers the break-even repayment, and ultimately is more inclusive and efficient. On the contrary, an institutional environment that limits a big techs' ability to retaliate and exclude from their ecosystem on the ground of protecting firms from powerful big techs, has the unintended consequence of encouraging strategic defaults by solvent firms, hence limiting their investment opportunities.

[12] We assume ρ is not too high such that these cut-offs remain below 1.

4 Competition between big techs and banks

We now move on to consider repayment competition between banks and informed big techs. We focus on a representative bank and a representative big tech assuming that both make zero expected profits.[13] As they compete in repayment, the big tech can draw the bank's clients by undercutting it. We will first show that firms will not borrow from an all too powerful big tech that learns the firm type p perfectly and privately. Then, in the following section, we will introduce noisy private learning to show that the big tech will optimally choose not to learn the firms' type perfectly. This would be to counteract the effect of its strong enforcement ability. Imperfect learning aims to leave sufficient information rent to firms to enable the big tech to compete against the bank and draw clients.

In this section, we assume that market shares are endogenously determined, and in Section 5.1, we study a formal limit on the market share of the big tech. In reality, the market share of big techs is restricted by two main institutional reasons: their debt capacity is quite limited as they cannot raise deposits lacking a banking license, and in some jurisdictions regulation and moral suasion limit their presence to some segments of the credit market.[14] Empirically, we observe that big techs serve a small, albeit growing, fraction of loans: for example, Frost (2020) shows that in 2017 the big techs

[13] Since the credit market is ex-ante competitive, we also rule out the possibility to tie-in access to e-commerce to credit. A big tech at $t = 0$ cannot exclude from its e-commerce a firm that does not want to borrow from the very same big tech.

[14] Big techs' relatively small lending footprint so far has reflected their limited ability to fund themselves through retail deposits. They could have the possibility to establish an online bank, but regulatory authorities could restrict the opening of remote (online) bank accounts. One relevant example is China, where the two Chinese big tech banks (Mybank and WeBank) rely mostly on the interbank market funding and certificates of deposit rather than on traditional deposits (Bank for International Settlements, 2019). Big Techs cannot issue virtual deposits which increases substantially their cost of funding (certificate of deposits and bonds are typically more costly than deposits). A second limitation is given by the fact that big techs cannot adopt a full originate-to-distribute model, partnering with banks. In principle, big techs could provide the customer interface and allow for quick loan approval using advanced data analytics; if approved, the bank could be left to raise funds and manage the loan. This option can be attractive to big techs as their platforms are easily scalable at low cost and they interface directly with the client. However, regulation could limit this practice imposing retention requirements for joint lending with banks. Commercial banks in China must jointly contribute funds to issue internet loans with a partner, and the proportion of capital from their partnership in a loan should not be less than 30%. Moreover, limits on banks' internet loans relative to tier-1 capital are also in place.

market share was around 2.7% in China, 2.2% in South Korea, 1.65% in US, and 1.1% in UK. Similarly, for fintech, Hau et al (2019) observe that in China in 2016 fintech credit represented only 0.37% of all credit to SMEs; Frost et al (2019) shows that fintech firms extend less than 1% of global private sector credit. In 2017 fintech and big techs combined accounted for only 0.14% of the total assets of the global financial system (Frost, 2020).

As mentioned, big techs have information advantages with respect to banks. For example, using data for Mercado Credito, which provides credit lines to small firms in Argentina on the ecommerce platform Mercado Libre, Frost et al (2019) find that, when it comes to predicting loss rates, credit scoring techniques based on big data and machine learning have so far outperformed credit bureau ratings. A number of studies show that even digital soft information has informational content that enhances credit scoring.[15]

Not only does a big tech have a better idea about the distribution of firm types, it also obtains a deep knowledge about each of its clients from the loan relationship. Anecdotal evidence indicates that a big tech understands the firm's type early on in the ecosystem, after a couple of years of knowledge in the payment platform, independently of the use of the credit line. In the next section we study learning types with noise.

We distinguish between two information sets for the big tech: the ability to identify whether a firm is solvent (solvency information) when it enters its ecosystem before lending, and the ability to identify its type (type information) after lending but before repayments. First, we capture solvency information in our setting by assuming that the big tech can assign loan applicants to two groups, solvent and insolvent, i.e. firms with $p \in [0, 1/Y)$, without identifying their true type, though. At $t = 0$ the bank faces types $p \in [0, 1]$, with density $f(p)$ and cumulative $F(p)$ while the big tech can exclude

[15] Dorfleitner et al (2016) study the relationship between soft factors in peer to peer (P2P) loan applications and financing and default outcomes. Using data on the two leading European P2P lending platforms, Smava and Auxmoney, they find that soft factors influence the funding probability but not the default probability. Jagtiani and Lemieux (2018) find that the ratings assigned on the basis of alternative data perform well in predicting loan performance over the two years after origination. The use of alternative data has allowed some borrowers who would have been classified as subprime by traditional criteria to be slotted into "better" loan grades, enabling them to benefit from lower priced credit. In addition, for the same risk of default, consumers pay smaller spreads on loans from LendingClub than from credit card borrowing. Berg et al (2020) show that digital footprints are a good predictor of the default rate. Analysis of simple, easily accessible variables from digital footprints is equal to or better than the information from credit bureau scores.

insolvent applicants and faces types $p \in [1/Y, 1]$ with conditional density $\frac{f(p)}{1-F(1/Y)}$. Second, after lending, the big tech may also identify a firm's true type between $t = 0$ and $t = 1$. This allows the big tech to demand a type-contingent repayment $R(p)$ if its private signal about the firm's type is perfectly accurate.

We assume that the big tech acquires privately either information set, an assumption that, as we will show, matters for the ability to contract on the repayment and on the architecture of information sharing. The amount of information available to the big tech plays a critical role in determining whether it can draw clients from the bank.

We assume that the big tech cannot commit at $t = 0$ to a repayment based on the type of the firm it will learn later. This implies that the big tech cannot commit to set a cap to the repayment. Furthermore, since the big tech learns the information privately, firms understand that it may gain by overstating the probability of success to extract all the firm's continuation value.

Let us specify the timing. At $t = 0$ the bank faces applicants with types $p \in [0, 1]$ while the big tech faces only applicants with types $p \in [1/Y, 1]$. If a firm borrows from the big tech, between $t = 0$ and $t = 1$ the big tech also identifies its true type and demands $R(p)$. Thus, anticipating $R(p)$, at $t = 0$ a firm of type p decides to borrow from the big tech or from the bank at a fixed repayment.

The $t = 0$ contract provides for a type-contingent repayment $R(p)$, where p will be announced after the big tech learns a firm's type. Without loss of generality, we assume that big tech is induced to announce p truthfully. Thus, the repayment function $R(p)$ for the big tech satisfies the following Principal's Incentive Compatibility constraint, or (PIC).[16] It captures the fact that a firm anticipates that the big tech cannot stop itself from using the information it has acquired privately about the firm and that it will charge the highest repayment it can. It characterizes $R(p)$ as the maximum repayment that the big tech can demand from any type $p \geq 1/Y$. Recalling that $\rho = 1$ for a big tech loan, the(PIC) is derived by replacing $R(p)$ for R in the firm (IC) :

$$Y - R(p) - 1 + pY = Y \Leftrightarrow pY - 1 = R(p), \text{ for } p \geq 1/Y. \qquad (PIC)$$

It follows that a firm with $p \geq 1/Y$, borrowing from the big tech, would be indifferent between repaying $R(p) = pY - 1$ at $t = 1$, or strategically defaulting. In other words, the big tech uses its available information to fully extract the firm's continuation value at $t = 1$ leaving the firm an expected payoff of pY from the first period of the relationship.

[16]See, e.g., Laffont and Martimort (2002, chapter 9.1), or Khalil et al (2015).

Again, insolvent firms with $p < 1/Y$ can only borrow from the bank, defaulting strategically if successful, and they earn an expected return ρpY. Types planning to default, choose to borrow from the bank as the post default option ρ is greater. Types planning to repay either type of lender compare the repayments to big tech and bank to realise that the bank provides a greater expected return.

To interpret the contract $R(p)$, it may sound at odds with reality that a borrower does not have an explicitly contacted repayment when offered a loan, but a borrower of type p will be able to anticipate at $t = 0$ what its repayment will be. Thus, we have the following result showing that too much information prevents big tech entry.

Proposition 1. If a big tech learns the firm type p *perfectly* and *privately,* all firms will borrow from the bank at the repayment $\underline{R}$ such that

$$\mathbb{E}\left(\Pi^{B}\right) = \int_{\frac{\underline{R}+1}{Y}+\rho-1}^{1} p\underline{R} f\left(p\right) dp - \int_{0}^{1} f\left(p\right) dp = 0. \tag{4}$$

Proof. See Appendix.

Two factors are at work here. First, the big tech cannot stop itself from using all the privately-learned information to demand a repayment rate to fully extract the firm's continuation value at $t = 1$. Model-wise this is captured by PIC. Second, the better post default options on a bank loan hurts the big tech. The combination of these two factors turns out to be too costly to the big tech ex ante.

Thus, we next move to studying the case where the big tech can commit to data privacy by choosing the precision of learning.

5 Noisy Signal Offers Privacy

In this section, we argue that the big tech have incentive to offer privacy, that is, it may want to learn the firm's type imperfectly to compete for the bank's clients. The precision with which the big tech learns about its clients depends on systems in place. We obtain two key lessons. First, it could be in the big tech's interest to limit what it learns about its clients even further than what is required by customer privacy laws and other relevant regulations. Second, since the strategic default option of each firm limits the repayment a big tech can ask, inefficient strategic defaults by solvent firms do not occur in a big tech loan. The only remaining inefficiency is due to insolvent firms obtaining a loan from the bank, which does not have the information to screen out such clients.

Financial intermediaries cannot include certain client specific characteristics in the information set to be used to train credit scoring models out of concern for issues of privacy and discrimination. For example, the US Fair Housing Act (FHA) and Equal Credit Opportunity Act (ECOA) prohibit credit scoring agencies from considering information like race, colour, religion, gender, marital status. The consumer credit scoring FICO voluntarily also excludes age, salary, occupation, title, employer, employment history, address. In either case the rationale is to avoid discrimination against applicants based on characteristics of groups with lower average scores. In our model instead, the rationale is to avoid extracting continuation values, i.e., strategically avoid price discrimination, against firms with high probabilities of success.[17]

To make our point in a stark manner, we assume zero (direct or physical) cost for the precision of learning. It would be straightforward to introduce costly learning without affecting our key insights.

We rely on a simple setting to illustrate our point. The intuition is that, to compete against the bank, the big tech chooses to acquire a limited amount of information at $t = 0$. The feasibility of self imposing limits on the collection of customers information is documented by steps taken by several big techs: for example Apple requires apps to ask users whether they want to be tracked, Facebook dropped face recognition, and Google plans to remove cookies that track online activity. In particular, limited learning enables the big tech to assure a client that it will not fully extract the firm's continuation value at $t = 1$. On this dimension, the big tech's advantage over the bank is given by $\rho - 1 > 0$. Thus to compete with the bank the big tech aims to leave a rent at least $(\rho - 1)\, pY$ to each type to which it lends. Thus, at $t = 0$, it sets up a technology to collect information that will generate a noisy signal ε about the firm type. This makes the big tech uncertain about the true type and prevents it from charging the maximum that a firm of that type can repay.

[17] A related topic is unfair price discrimination. Sophisticated machine learning algorithms may not be as neutral as their mathematical nature suggests at first glance. Even though artificial intelligence and machine learning algorithms are neither trained nor fed with protected characteristics such as race, religion, gender, or disability, they are able to triangulate such information. Using data on US mortgages, Fuster et al (2019) find that black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning in credit scoring models, suggesting that the algorithm may develop differential effects across groups and increase inequality.

A model of noisy learning would work as follows. For each type $p \geq 1/Y$, the big tech draws a signal s about the firm from the interval $[p-\varepsilon, p+\varepsilon]$, such that $\mathbb{E}[s|p] = p$.[18] As in the case with perfect learning of type, the big tech's signal-contingent repayment $R(s)$ can be derived from a principal's incentive constraint, but modified to allow for noisy learning. The constraint is now denoted as (PIC'). Again, it captures the maximum repayment $R(s)$ such that no solvent type has an incentive to default strategically

$$Y - R(s) - 1 + (s-\varepsilon)Y \geq Y, \tag{PIC'}$$

which yields

$$R(s) = \max\left(0, (s-\varepsilon)Y - 1\right). \tag{5}$$

In addition to ensuring that a firm of type p does not default strategically, the repayment $R(s)$ must also leave no incentive to borrow from the bank. Thus, the expected repayment must have a large enough discount to attract as many solvent firms as possible from the bank.

Since the repayment $R(s)$ cannot be negative, some firms in $p \in [1/Y, 1/Y+\varepsilon]$ will prefer to borrow from the bank and strategically default. That is, there exists a firm of type $p_0 \in (1/Y, 1/Y+\varepsilon)$ which is indifferent from borrowing from the big tech at $R(s) = 0$, and borrowing from the bank and then defaulting strategically:

$$\underbrace{p_0\left(Y + p_0 Y - 1\right)}_{\text{borrowing from big tech at } R(s)=0} = \underbrace{p_0 Y \rho}_{\text{borrowing and defaulting from bank}} \Rightarrow$$

$$p_0 = \frac{1}{Y} + \rho - 1. \tag{6}$$

This allows us to establish the following result:[19]

Proposition 2. Under noisy and private type learning by the big tech, there exists both a $p_0 = \frac{1}{Y} + \rho - 1 \in (1/Y, 1/Y+\varepsilon)$, and a $p_b = \frac{R^B+1}{Y} + \varepsilon \in (1/Y+\varepsilon, 1)$ such that firms choose to borrow from the bank or the big tech depending on their types as follows:

- All firms with $p \in [0, p_0)$, (that we label Group 1) borrow from the bank.

[18] For completeness we specify the expectation of signals at the top extreme by assuming that $E[s|p] = 1$ for all $p \in [1-\varepsilon, 1]$. These latter types will not be relevant for the Big Tech in equilibrium. They will strictly prefer to borrow from the bank unless the noise is very large.

[19] Existence of the competitive equilibrium of Proposition 2 is illustrated in a numerical example in Appendix.

- All firms with $p \in [p_0, p_b]$, (Group 2) borrow from the big tech at a signal-contingent rate (5) and do not default strategically.
- All firms with $p \in (p_b, 1]$, (Group 3) borrow from the bank at the break even rate R^B and do not default strategically.
- In equilibrium $\varepsilon > \rho - 1$, where ε is determined by the zero expected profit conditions of the bank and big tech ((11) and (12) and in the Appendix).

Proof. See Appendix.

For an illustration of Proposition 2 see Figure 1.

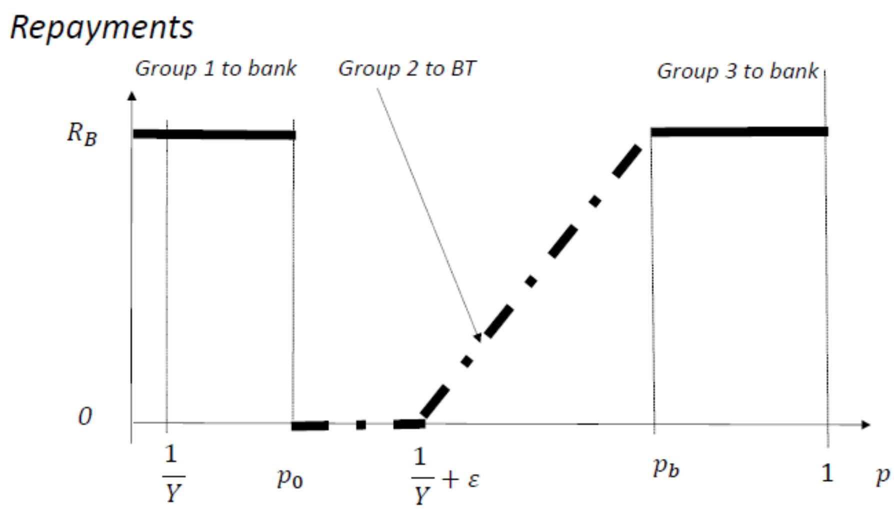

Figure 1: Proposition 2. Riskiest and safest firms borrow from the bank at R^B. Middle risk firms borrow from big tech at $R(s) = \max(0, (s-\varepsilon)Y - 1)$. Recall that $p_0 = \frac{1}{Y} + \rho - 1$ and $p_b = \frac{R^B+1}{Y} + \varepsilon$.

Several comments are in order. First, our result is linked to one of the themes of the research on privacy and price discrimination, namely that firms often benefit from committing to privacy policies (Acquisti et al, 2016). Collecting anonymous data with aggregate, market-level information prevents the seller to set personalized prices (Bergemann et al, 2021). Federated machine learning plays a similar role by filtering information without revealing the identity.

Second, in Groups 2 and 3 we have an efficient outcome whereby solvent firms do not strategically default. This is because the big tech internalizes, via PIC, each firms' option to default strategically. Inefficiency arises as the bank funds insolvent firms in Group 1.

Third, our results fit stylized industry facts. It is widely accepted that the big techs are able to identify firm's types, which allows them to classify firms better than banks, particularly the riskiest firms (Frost et al, 2019). In Proposition 2 the riskiest firms are excluded from the big tech loans at $t = 0$ but not from bank loans.

Finally, another stylized fact is that the safest firms borrow from the banks.[20] Indeed Group 3 firms prefer to borrow at a fixed rate from the bank rather than suffering the extraction of the continuation value from the big tech.

5.1 Big tech with restricted market share

In this subsection, we consider the case where the big tech can serve at most a "small" fraction $\alpha \in (0, 1)$ of randomly selected firms of each types p, while the bank serves a complementary fraction. As argued earlier in Section 5, there is reason to believe that there are currently policy and institutional limits to the market share of big tech. Indeed, Hau et al (2019) also assume an exogenous limit on market share in their analysis of firms borrowing from their ecommerce platforms companies.

Unsurprisingly, our qualitative results largely remain unaffected w.r.t. Proposition 2, except that the big tech must share medium-risk firms (Group 2) with the bank due to the cap α on its market share. Details are in Corollary 1 and in a related numeral example (See the Appendix). Here we report two main findings. First, regulatory caps on the big tech market share have welfare costs because the riskiest firms in Group 2 default strategically when they borrow from the bank. Second, in a numerical example, we find that as the binding limit α decreases from 1, the big tech encroaches further into the bank's low-risk pool (Group 3) in order to break even.

[20] Jagtiani et al (2019) find that fintech lenders in the United States tend to supply more mortgages to consumers with weaker credit scores than do banks; they also have greater market shares in areas with lower credit scores and higher mortgage denial rates.

5.2 Big tech with market power

In this sub-section, we study the case where the big tech has market power and focus on the impact on privacy, i.e. the level of noise ε. Detailed arguments are relegated to the Appendix. For simplicity, we assume that the big tech is a monopoly while the bank remains competitive and makes zero profit in expectation. The key aspects of our analysis remain unaffected. Namely, the characterization of the three groups of firms remains unchanged and the big tech continues to rely on privacy to lure low-risk firms away from the bank. We find that the big tech will strategically increase or decrease privacy depending on how strongly the bank's break-even rate R^B is affected by a change in privacy. In the Appendix, we provide a numerical example suggesting that privacy will increase when the proportion of low-risk firms the big tech can attract by increasing privacy is high.

We outline the intuition first. Recall that the big tech competes for low-risk firms by offering privacy, or learning imprecisely, but doing so lowers the payment $Y(p-\varepsilon)$ from each type. When the big tech increases ε, some of the bank's low-risk customers switch to the big tech, the bank's profit decline, and the break-even rate for the bank R^B must increase. When a small change in ε calls for a large change in R^B to satisfy the break-even condition for the bank, it is convenient for the big tech to increase ε. The resulting large increase in R^B significantly raises the mass of low risk firms that it lures away from the bank. That is, a small sacrifice on the payment $Y(p-\varepsilon)$ buys the big tech a large gain in the mass of low risk firms. Then, the big tech will gain by increasing privacy. When, on the contrary, a large change in ε induces only a small change in R^B, then the big tech gains by offering lesser privacy, accepting to lose some low risk firms on the extensive margin, to increase the payment $Y(p-\varepsilon)$ from the firms it serves. Hence the big tech will choose to learn more precisely.

To see more details, note that the payment structure remains similar to the case under competition. Recall that the big tech chooses its payments accounting for each type's incentive to default, modulo noisy learning, whereas the bank must charge the same R^B to all firms that borrow from it. A firm borrowing from the big tech retains surplus only due to imperfect learning by the big tech. Borrowing at the bank's break-even rate R^B, the lower-risk firms retain a surplus, and this surplus increases with p. The big tech's mass of low-risk firms is determined by the type $p_b = \frac{R^B+1}{Y} + \varepsilon$, where a firm with type p_b is indifferent between repaying R^B on a bank loan or borrowing from the big tech. Thus, an increase in R^B or an increase in noise ε, increases p_b, hence increasing the low-risk firms that borrow from the big tech.[21] This interaction is identical to that under competition. The key difference when the big tech has market power is in ε, the degree of privacy.

Technically, in a stable equilibrium, the bank's profit is increasing in R^B for a given ε. To see this, observe that an increase in ε increases p_b and decreases the mass of bank's low-risk firms. This reduces the bank's profit below zero, and R^B must change for the bank to break even. Since the equilibrium would not be stable if the bank could lower R^B and increase profit, it must be that the profit is increasing in R^B in a stable equilibrium.

Finally, in Appendix we provide a numerical example to highlight the intuition above by changing the proportion of low-risk firms. We show that the big tech increases ε relative to the case under competition with a uniform distribution of types, while the opposite is true when the proportion of low-risk firms decreases with type, and the big tech does not gain as much by increasing privacy.

To sum up, whether the monopoly big tech will increase or decrease privacy w.r.t. the competitive equilibrium depends on the relative importance of two effects. By offering more privacy the big tech lures some low-risk firms away from the bank, but it accepts a lower repayment from all the firms. If the first effect dominates the monopolist big tech will offer more privacy w.r.t. the competitive equilibrium, and vice versa if the second effect dominates. Which effect dominates depends on the strength of the reaction that a change in privacy triggers on the R^B to keep the bank on its break-even condition. If a small change in privacy triggers a large change in R^B, by offering more privacy the big tech lures many low-risk firms away from the bank which increases the big tech profit as it can compensate for the loss on the repayment.

We now move on to explore information sharing from big techs to banks.

6 Information sharing

Big techs and banks have complementary advantages. In the previous sections we have explored the implications of the superior enforcement of the big techs. Here we focus on other relative advantages of big techs and banks: from ecommerce, big techs

[21] Only solvent firms are affected by the degree of privacy since the big tech only lends to such firms. The lower margin of big tech lending, less relevant to our key point, is determined by high-risk solvent firms deciding between borrowing from the big tech or defaulting on a bank loan.

receive troves of data while banks largely fund themselves with cheap deposits that the big techs cannot access. Lack of access to deposits makes big techs funding more costly than banks funding and it is a factor limiting their supply of lending. Lack of information would result in banks funding insolvent firms. Thus, it seems natural to investigate whether it is possible to exploit these relative advantages so that the big techs gather the raw data, process them and share the relevant information with the banks that make loans funded with deposits.

We focus on a representative bank and a representative big tech assuming that each type of lender makes zero expected profits. We consider two cases of information sharing by the big tech: (i) firm type p can only be *privately* communicated to the bank, e.g. because the information is soft and (ii) firm type p is verifiable and can be made *public*. The key difference is that banks cannot commit to $R(p)$ in the first case while they can commit to an $R(p)$ based on publicly observed p in the second case.[22]

We start with the case where the firm type p can only be *privately* communicated to the bank. Circumventing the delicate issue of trading soft information, we simply assume that the bank forms a joint venture with the informed big tech.[23] By doing so, they can exploit their mutual advantages.[24] Since this information remains private, the bank cannot commit at $t = 0$ to a $R(p)$, but this rate will again be determined by a principal's incentive constraint or PIC, which is constrained by a type-p firm's strategic default option at the interim stage. As in the case of Proposition 2, with a big tech learning the type privately, the venture between bank and a big tech attains zero expected profits by offering privacy to their clients in the form of noisy learning.[25]

Two comments are in order. First, since PIC accounts for the firms' option to default strategically we obtain the first best as all solvent firms are funded and there is

[22] In all cases we assume that the big tech has and shares solvency information like in the previous sections. We will clarify below when it matters whether information is available as a result of the relationship in the big tech ecosystem, that is after lending, as in the previous sections, or it is available before lending.

[23] The private information of the big tech is an extreme case of soft information about which the principal's and agents evaluations do not concur. MacLeod (2003) shows that in this case the optimal contract between principal and agent results in more compressed pay relative to the case of more verifiable performance measures. More broadly, the bank's obtaining soft information reliably from the big tech would require contingent payments which would be challenging to enforce.

[24] This is reminiscent of the regulation by which Chinese autorithies have imposed a minimal "skin in the game" for big techs. The latters have to provide a minimum amount of funding for the loans they make together with banks in the so called "originate to distribute" model.

[25] The venture learns type information with a noise denoted by δ, determined by the bank zero profit

no strategic default (as in Proposition 2). Second, when information is shared privately, unregulated ex ante competition will prove sufficient to yield the first best, which is not the case when information is available to the public, the case we analyze next.[26]

If information must or can be available to the *public* (for example via a public credit bureau or a public "data lake") then type information becomes contractible. Therefore, competition à la Rothschild-Stiglitz leading banks to break-even on each type would result in inefficiency in lending. This is because the break-even rate exceeds the rate that would prevent the riskiest solvent firms to default strategically. To understand the mechanics of this result, recall that in this model there are two sources of asymmetric information: about the firm type and about the firm output. Lack of output information leads to a problem of contract enforcement. A credit bureau that makes type information public eliminates the first source of asymmetric information, but not the contract enforcement problem. Once type information is available to the bank, a break-even rate for each type would mean that riskier firms must be charged more. It turns out that the break-even repayment for the riskiest firms exceeds the rate that induces them not to default strategically (see the discussion around Figure 2 below). Hence, solvent but risky firms will have incentive to default strategically at the break-even rate.

Thus, we find that if firm type information is made public when enforcement problems cannot be eliminated, unregulated ex ante competition will lead to inefficiencies. This is another example of a familiar result in markets where too high interest rates would lead to opportunistic behavior (e.g. due to moral hazard, strategic default) or adverse selection of borrowers, and rationing arises as a result.[27]

---

condition below,

$$\mathbb{E}(\Pi) = \frac{1}{1-F(1/Y)}\left[\int_{\frac{1}{Y}+\delta}^{1} pR(p)\, f(p)\, dp - \int_{\frac{1}{Y}}^{1} f(p)\, dp\right] = 0,$$

where a firm of type p anticipates the its rate $R(p) = \max(Y(p-\delta)-1, 0)$. Note that this condition holds regardless of whether the type information is available before lending or afterwards before repayment is due. When $Y(p-\delta)-1<0$ firms are allowed to continue by paying $R(p)=0$.

[26] When information is shared early, before lending, one may think that that the bank has no incentive to lend to solvent firms on which it knows is going to lose. However, since information is learned privately the bank is the only one that knows p, hence it cannot commit to $R(p)$ and later it will charge the maximum consistent with PIC; ex ante competition will determine δ and our qualitative results remain unchanged.

[27] Stiglitz and Weiss (1981) show that banks prefer to ration credit under adverse selection rather than increase interest rates and lose the safest firms. Diamond (1981) shows that under moral hazard lenders prefers to ration credit rather than increasing rates and trigger the choice of riskier projects.

We then explore whether and how *regulation* may mitigate these inefficiencies. The key is to sustain a repayment that both satisfies the incentive not to default strategically and allows the bank to break even in expectation. The $R(p)$ the bank will contract on is determined to solve its zero profit subject to the (IC), namely,

$$\begin{aligned} &\frac{1}{1-F(1/Y)}\left[\int_{\frac{1}{Y}}^{1} pR(p)\, f(p)\, dp - \int_{\frac{1}{Y}}^{1} f(p)\, dp\right] = 0 \\ &s.t. \qquad Y(p-(\rho-1))-1 \geq R(p)\,. \end{aligned} \tag{7}$$

As this $R(p)$ entails cross-subsidization, unregulated competition would destabilize this equilibrium since there is the familiar opportunity for cream-skimming.[28] To prevent competition from breaking the cross-subsidy, there must be a regulated scheme where banks register simultaneously and independently the contracts they wish to offer, with no room to add or subtract subsequently (See for example Kreps, 1990, for the general argument for contracts that entail cross subsidies).

The reason why unregulated competition leads to inefficiencies only when information is shared publicly stems from the fact that with "private information sharing" the joint venture between the bank and the big tech can do cross subsidy that cannot be destroyed by competition. In fact a potential entrant cannot commit not to charge the maximum repayment since the information that it would learn is private and thus cannot be contracted upon.

Note that there would also be efficient lending if the joint venture were a monopolist since competition between banks would not get in the way of internalizing the impact of strategic default. Then, the lender would not have to break even on each type – then $R(p) = Y(p-(\rho-1))-1 < 1/p$ to avoid strategic default.

Technically, the nature of inefficiency with competitive lending under public info depends on when the joint venture receives the type info. We briefly clarify this point before closing the section. If the type information is available before lending, we find that a joint venture will choose not to lend the riskiest solvent types. Competition between banks leads to a break-even condition for each type of firm: $R(p) = 1/p$. However, Incentive Compatibility requires that $R(p) \leq Y(p-(\rho-1))-1$. That is, solvent types $p \in [1/Y, p^*)$ will be rationed at $t=0$, where type p^* is indifferent between repaying $R(p^*) = 1/p^*$ and be allowed to continue or defaulting strategically to obtain $Y\rho$. Figure 2 illustrates this point.

[28] Some bank could undercut others by lowering $R(p)$ for the highest p, making it impossible to break even for the bank continuing to serve only the remaining lowest p.

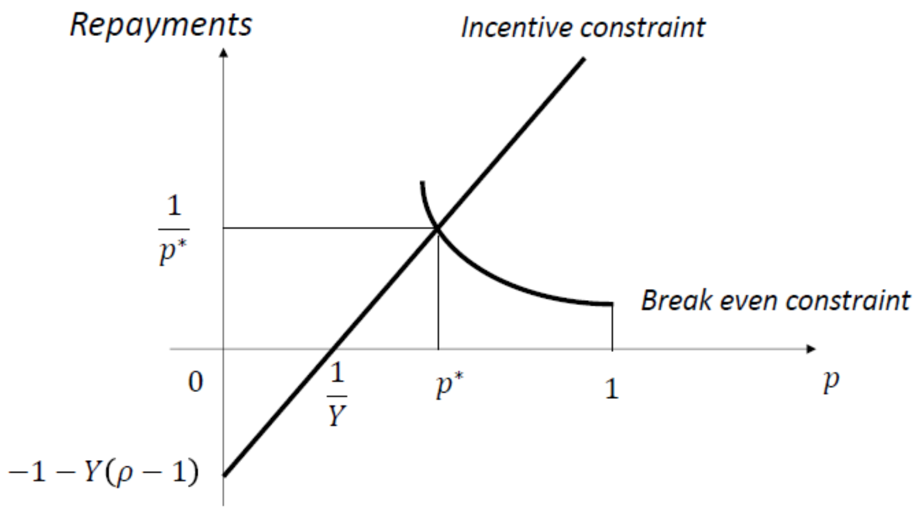

Figure 2: Big tech shares information publicly with a bank

If the type info arrives after lending but before payment is due, the bank can still contract on a repayment $R(p)$ at the outset based on p that will be revealed later. However, the bank cannot prevent a solvent firm from borrowing and defaulting strategically. Since the break-even rate induces strategic defaults for $p \in [1/Y, p^*)$, the bank cannot break even in expectation without cross-subsidies. However, a pure-strategy equilibrium with cross-subsidies does not exist as it is vulnerable to cream-skimming. Thus, we can again argue for regulation to preserve a cross-subsidy based payment scheme that includes all solvent firms.

We end this section by stressing that even when information is shared publicly the big tech should share information, i.e. processed data like credit scoring, rather than the raw data in case it is too costly to process the raw data. Data processing for credit scoring could have high fixed costs to set up the necessary IT infrastructure and create a highly specialized team. For this reason it could be costly for a bank to extract information from the raw data and a joint venture in which the big tech shares the information rather than the data would be advisable.

7 Conclusions

We have modeled competition between banks and big techs in a credit market where adverse selection and difficulty of enforcing repayment cause frictions. We have obtained three main results.

First, more powerful retaliation after a default increases welfare as it lowers the fraction of solvent firms that strategically default (Lemma 1). This result implies an extreme form of exclusivity where a firm cannot access ecommerce through one big tech after defaulting on a loan from another big tech. Lemma 1 has the counterintuitive implication that regulations limiting a big tech's ability to exclude defaulting firms from its ecosystem encourages inefficient strategic defaults by solvent firms. However, the exclusivity of the agreements between big techs and firms may lead to monopoly distortions in access to ecommerce. For this reason, for example, regulators in China have blocked the "choose one from two" restriction whereby an ecommerce platform can prevent a firm from selling through another platform. Our model doesn't capture the monopoly distortion of exclusive dealing as we don't price access to ecommerce. Thus, if extending credit is the main policy objective there is a case for exclusivity. If, on the contrary, the main policy objective becomes preventing monopoly distortions in access to ecommerce there is a case to eliminate exclusivity. That is as the credit footprints of big techs grow, the exclusivity in enforcing repayment its loses importance.

Second, too much information damages the big tech. Firms will not borrow from a big tech that by learning their type perfectly (and privately) can extract all the continuation value (Proposition 1). The ex-ante competitive threat of banks prevent big techs from charging very high rates to the safest firms (Proposition 2). To enter bank's turf big techs must therefore self-regulate by credibly committing to data privacy to limit their exploitation of firms.

Third, extending our basic framework to big techs with market power, we found that results are qualitatively similar to those under perfect competition. In fact, regardless of market power the repayment that an informed big tech can demand is capped by the possibility that the firm could strategically default minus a rent to induce the firm not to borrow from the bank. Therefore, when the big tech maximizes its expected profit subject to the zero expected profit condition of the bank, the only change will be in the size of the regions of the firm types that borrow from big tech and bank.

Finally, our model points to information sharing as a way to mitigate the tension between privacy and efficiency. We have explored two information-sharing arrangements from big techs to banks. This aspect is particularly relevant in light of the ongoing debate on the trade-offs and limits of alternative information arrangements. Our conclusion is in the tradition of the literature that shows the peril that competition will destroy solutions based on cross-subsidies. In the presence of limitations in the judicial system, we show that it is preferable not to make information public; rather it is better to regulate competition to permit the cross-subsidies that allow exploiting all gains from trade.

In order focus on the trade-off between data privacy and efficiency in a simple framework, we remain silent on many related issues that deserve further investigation. First, we have taken as given the network externalities stemming both from the ecommerce and the payments systems run by the big techs. Second, we have not modeled data externalities. Data externalities refer both to the fact that information about an individual helps when seeking to understanding the characteristics of others (Hagiu and Wright, 2020; Brunnermeier et al, 2020; Bergemann et al, 2021) and to the fact that information about others helps the individual, as with Google traffic data. Third, we did not answer the question of how to regulate big techs in the financial world. In particular, on the funding side we do not model capital regulation and deposit insurance and the related financial stability concerns, issues that are growing in importance with the growing financial footprint of big techs in some jurisdictions. Fourth, we model big techs and banks as direct competitors. However, the analysis of information sharing captures the business model of a big tech that is mainly an information intermediary collecting service fees. As such, even if we do not consider fees as they are welfare irrelevant in this setting, our model nonetheless captures some of the elements of the Ant Group's business model in China, where banks provide the bulk of the funding and take a substantial part of the credit risk. The analysis of the optimal business arrangement between banks and big techs is one relevant area for future research.

References

Acquisti, A., and H.R. Varian (2005). "Conditioning Prices on Purchase History," *Marketing Science*, 24, 367-381.

Acquisti, A., C. Taylor, and L. Wagman (2016). "The economics of privacy," *Journal of Economic Literature*, 54, 442-492.

Argenziano, R. and A. Bonatti (2021). "Data Linkages and Privacy Regulation" mimeo.

Belleflamme, P., N. Omrani, and M. Peitz (2016). "The Economics of Crowdfunding Platforms," CESIfo DICE Report, Volume 14.

Bergemann, D. Bonatti, A., and T. Gan (2021). "The Economics of Social Data," mimeo, Yale University, January.

Berg, T., V. Burg, A. Gombović, and M. Puri (2020). "On the rise of fintechs – credit scoring using digital footprints," *The Review of Financial Studies*, 33, 2845-2897.

Bank for International Settlements (2019). "Big tech in finance: opportunities and risks," *Annual Economic Report*, Chapter III, June.

Bolton, P., and D. Scharfstein (1990). "A theory of predation based on agency problems in financial contracting," *The American Economic Review*, 80, 93-106.

Bolton, P., X. Freixas, L. Gambacorta, and P. E. Mistrulli (2016). "Relationship and Transaction Lending in a Crisis," *The Review of Financial Studies*, 29, 2643–2676.

Calzolari, G. and A. Pavan (2006). "On the Optimality of Privacy in Sequential Contracting," *Journal of Economic Theory*, 130, 168-204.

Carrillo, J.D. and T. Mariotti (2000). "Strategic Ignorance as a Self-Disciplining Device," *Review of Economic Studies*, 67, 529-544.

Carstens, A. (2018). "Big tech in finance and new challenges for public policy," Keynote address, FT Banking Summit, London, 4 December 2018.

Carstens, A., S. Claessens, F. Restoy, and H.S. Shin (2021). "Regulating big techs in finance," BIS Bulletin, No 45.

Cole, H. and P. Kehoe (1995). "The role of institutions in reputation models of sovereign debt," *Journal of Monetary Economics*, 35, 45-64.

Cornelli, G., J. Frost, L. Gambacorta, R. Rau, R. Wardrop, and T. Ziegler (2020). "Fintech and big tech credit: a new database," BIS, Working paper No 887.

Cornelli, G., J. Frost, L. Gambacorta, C. Mu, and T. Ziegler (2021). "Big tech credit during the Covid-19 pandemic," mimeo.

Dorfleitner, G., C. Priberny, S. Schuster, J. Stoiber, M. Weber, I. de Castro, and J. Kammler (2016). "Description-text related soft information in peer-to-peer lending – Evidence from two leading European platforms," *Journal of Banking and Finance*, 64, 169-87.

Feyen, E., J. Frost, L. Gambacorta, H. Natarajan, and M. Saal (2021). "Fintech and the digital transformation of financial services: implications for market structure and public policy," BIS, Working paper, No 117.

Fong, Y., K. Liu, X. Meng, and K.Y. Tam (2021). "FinTech Lending and Financial Inclusion," mimeo, March.

Frost, J., L. Gambacorta, Y.L. Huang, H.S. Shin, and P. Zbinden (2019). "big tech and the changing structure of financial intermediation," *Economic Policy*, 34, 761-99.

Frost, J. (2020). "The economic forces driving fintech adoption across countries," BIS, Working paper, No 838.

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther (2019). "The effect of machine learning on credit markets," VoxEU, 11 January 2019.

Gambacorta, L., Y. Huang, Z., Li, H. Qiu, and S. Chen (2020). "Data vs collateral," BIS, Working paper, No 881.

Hagiu, A. and J. Wright (2020). "Data-enabled learning, network effects and competitive advantage," mimeo.

Hau, H., Y. Huang, H. Shan, and Z. Sheng (2019). "How FinTech Enters China's Credit Market," *AEA: Papers and Proceedings*, 109, 60-64.

He, Z., J. Huang, and J. Zhou (2020). "Open Banking: Credit Market Competition When Borrowers Own the Data," Working paper, No 168, Becker Friedman Institute, University of Chicago.

Huang Y., C. Lin, Z. Sheng, and L. Wei (2018). "FinTech Credit and Service Quality," mimeo.

Jagtiani, J., and C. Lemieux (2018). "The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform," Federal Reserve Bank of Philadelphia, Working Papers, 18–15, April.

Jagtiani J., L. Lambie-Hanson, and T. Lambie-Hanson (2019). "Fintech lending and mortgage credit access," Federal Reserve Bank of Philadelphia Working Papers, 19-47, November.

Jappelli, T., and M. Pagano (2002). "Information sharing, lending and defaults: Cross-country evidence," *Journal of Banking and Finance*, 26, 2017-2045.

Khalil, F., J. Lawarrée, and T.J. Scott (2015). "Private monitoring, collusion, and the timing of information," *RAND Journal of Economics*, 46, 872-890.

Laffont, J-J., and D. Martimort (2002). *The Theory of Incentives*, Princeton University Press.

Myers, S., and R.G. Rajan (1998). "The Paradox of Liquidity," *Quarterly Journal of Economics*, 113, 733-771.

Pagano, M., and T. Jappelli (1993). "Information sharing in credit markets," *The Journal of Finance*, 48, 1693-1718.

Parlour, C.A., H. Rajan, and H. Zhux (2020). "When FinTech Competes for Payment Flows," mimeo February.

Philippon, T. (2020). "On fintech and financial inclusion," BIS, Working paper No 841, Monetary and Economic Department.

Sharpe, S.A. (1990). "Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships," *The Journal of Finance*, 45, 1069–1087.

Taylor, C. R. (2004). "Consumer privacy and the market for customer information," *RAND Journal of Economics*, 35, 631-650.

Townsend, R. M. (1979). "Optimal contracts and competitive markets with costly state verification," *Journal of Economic Theory*, 21, 265–293.

Vives, X. and Z. Ye (2021). "Information Technology and Bank Competition," mimeo.

Von Thadden, E. L. (1995). "Long-term contracts, short-term investment and monitoring," *Review of Economic Studies*, 62, 557–575.

Yu, S. and R. Mc Morrow (2021). "Beijing to break up Ant's Alipay and force creation of separate loans app," Financial Times, 13 September.

Zetzsche, D.A., R.P. Buckley, D.W. Arner, and J.N. Barberis (2017). "From FinTech to TechFin: The Regulatory Challenges of Data-Driven Finance," EBI Working Paper Series – no. 6.

Appendix

A.1 Proof of Lemma 1

The zero expected profit condition for a representative lender determines the break-even repayment rate R:

$$\mathbb{E}(\Pi) = \int_{\frac{R+1}{Y}+\rho-1}^{1} pRf(p)\,dp - (1+r)\int_0^1 f(p)\,dp = 0. \tag{8}$$

Differentiating (8) with respect to the parameter ρ we have

$$\frac{dR(\rho)}{d\rho}\left[\left\{\int_{\frac{R(\rho)+1}{Y}+\rho-1}^{1} pf(p)\,dp\right\} - \frac{R(\rho)}{Y}\left(\frac{R(\rho)+1}{Y}+\rho-1\right)f\left(\frac{R(\rho)+1}{Y}+\rho-1\right)\right]$$
$$= \underbrace{R(\rho)\left[\frac{R(\rho)+1}{Y}+\rho-1\right]f\left(\frac{R(\rho)+1}{Y}+\rho-1\right)}_{>0}.$$

Observe that the coefficient of $\frac{dR(\rho)}{d\rho}$ on the LHS is positive as $\frac{R(\rho)}{Y} < 1$, and the term $\left(\frac{R(\rho)+1}{Y}+\rho-1\right)f\left(\frac{R(\rho)+1}{Y}+\rho-1\right)$ is the value of the function $pf(p) > 0$ in the integral $\int_{\frac{R(\rho)+1}{Y}+\rho-1}^{1} pf(p)\,dp$ evaluated at its lower limit. Hence we have $\frac{dR(\rho)}{d\rho} > 0$, from which we also have that $\widehat{p} = \frac{R(\rho)+1}{Y}+\rho-1$ increases with ρ. End of proof.

A.2 Proof of Proposition 1

Consider each type of firm's choice between the bank and the big tech. Again, firms with $p \in [0, \frac{1}{Y})$ will be detected and excluded by the big tech while they can borrow from the bank. If successful they will strategically default at $t=1$, and they can expect to obtain ρpY at $t=0$ from a bank loan. If firms with $p \in \left[\frac{1}{Y}, 1\right]$ borrow from the big tech they are fully exploited as they will have to repay $R(p) = pY - 1$ with an expected return pY at $t=0$.[29] What they obtain if they borrow from the bank depends on their type: firms with $p \in \left[\frac{1}{Y}, \frac{R+1}{Y}+\rho-1\right]$ will strategically default on a bank loan to obtain $p\rho Y$; firms with $p \in \left[\frac{R+1}{Y}+\rho-1, 1\right]$ enjoy a rent from the bank (zero rent only for types $p = \frac{R+1}{Y}+\rho-1$) at the reinvestment stage. Hence, firms with $p \in \left[\frac{1}{Y}, 1\right]$ have no incentive to borrow from the big tech. End of proof.

[29] It follows from $pY = p[Y - (pY-1) + (pY-1)]$.

A.3 Proof of Proposition 2

We analyze the behavior of the three groups of firms separately and then we derive the zero expected profit conditions of the bank and the big tech.

Group 1. Recall that $p_0 = \frac{1}{Y} + \rho - 1$. Firms $p \in [0, \frac{1}{Y})$ are cutoff from the big tech. From (6) firms $p \in [\frac{1}{Y}, p_0)$ prefer to borrow from the bank and default strategically.

Group 2. Let us start with the riskiest firms in Group 2. For $p \in [p_0, \frac{1}{Y} + \varepsilon)$, the big tech's expected repayment is 0.[30] Consider now the safest firms in Group 2. Define a marginal type p_b by

$$p_b = \frac{R^B + 1}{Y} + \varepsilon, \tag{9}$$

where the type p_b is indifferent between borrowing from either lender with no strategic default:

$$\underbrace{Y - R^B - 1 + p_b Y}_{\text{from bank}} = \underbrace{Y - (p_b - \varepsilon)Y + p_b Y}_{\text{from big tech}}. \tag{10}$$

Thus all types $p \in [\frac{1}{Y} + \varepsilon, p_b)$ prefer to borrow from the big tech. For each $p \in [\frac{1}{Y} + \varepsilon, p_b)$, the expected repayment to the big tech is $\mathbb{E}[R(s)|p] = Y(p - \varepsilon) - 1$.

Group 3. From (10) firms with $p \in (p_b, 1]$ strictly prefer to borrow from the bank at R^B.

Finally, the bank repayment R^B, and the big tech noisy learning ε, are jointly determined by the two $ZEPs$,

$$\mathbb{E}\left(\Pi^B\right) = \underbrace{\int_{p_b}^{1} \left[pR^B - 1\right] f(p)\, dp}_{\text{Group 3}} - \underbrace{\int_{0}^{p_0} f(p)\, dp}_{\text{Group 1}} = 0, \tag{11}$$

$$\mathbb{E}\left(\Pi^P\right) = \underbrace{\frac{1}{1 - F(1/Y)} \left[\int_{\frac{1}{Y}+\varepsilon}^{p_b} p\left(Y(p - \varepsilon) - 1\right) f(p)\, dp - \int_{p_0}^{p_b} (1 + r) f(p)\, dp\right]}_{\text{Group 2}} = 0, \tag{12}$$

[30] From $R(s) = \max(0, (s - \varepsilon)Y - 1)$, we have, for $p \in [\frac{1}{Y} + \rho - 1, \frac{1}{Y} + \varepsilon)$

$$\mathbb{E}[R(s)] = \max(0, (p - \varepsilon)Y - 1) = 0.$$

where the first zero expected profit condition is for the bank and the second is for the big tech.

Finally, $\varepsilon > \rho - 1$. This is because if $\varepsilon = \rho - 1$, the solution for R^B generically would not satisfy (12) and (11). End of proof.

A.4 Existence of equilibrium of Proposition 2

To show the existence of the competitive equilibrium of Proposition 2 we resort to the following calibrations. We assume that the density function of p is $f(p) = \gamma p^{\gamma-1}$. We take $\gamma = 1$ that is we assume that p is distributed as a Uniform in the interval $[0,1]$. We take $Y = 30$, and $r = 1\%$. We also assume that $\rho = 1.5$ which implies that $\varepsilon \geq 0.5 = \rho - 1$. With unlimited market share of the big tech, the zero expected profit conditions of bank and big tech, (11) and (12) are, respectively,

$$\int_{\frac{R+1}{30}+\varepsilon}^{1} \left(pR^B - 1\right) 1p^{1-1}dp - \int_{0}^{\frac{1}{30}+1.5-1} 1p^{1-1}dp = 0$$

$$\frac{1}{1-1/30}\left(\int_{\frac{1}{30}+\varepsilon}^{\frac{R^B+1}{30}+\varepsilon} p\left(30\left(p-\varepsilon\right)-1\right)1p^{1-1}dp - \int_{\frac{1}{30}+1.5-1}^{\frac{R^B+1}{30}+\varepsilon} \left(1+0.01\right)1p^{1-1}dp\right) = 0.$$

The solution is $R^B = 4.9082, \varepsilon = 0.65233$ which yields

$$p_b = \frac{R^B+1}{Y} + \varepsilon = p_b = \frac{4.9082+1}{30} + 0.65233 = 0.84927 < 1.^{31}$$

A.5 Big tech with market power

Here we sketch the arguments for the monopoly big tech case with the bank subject to break-even. We show that the big tech may gain by increasing or decreasing ε from the level that we obtain when the big tech must earn zero profit.

First, as in the case when the big tech has no market power, the repayment rate demanded by the big tech is determined taking into account a firm's incentive to default strategically:

$$R(s) = \max\left(0, (s-\varepsilon)Y - 1\right). \tag{13}$$

[31] We reported the only acceptable pair (R^B, ε). The entire set is: $\left[R^B = -9.7212, \varepsilon = -0.96370\right]$, $\left[R^B = -91.468, \varepsilon = 1.9880\right]$, $\left[R^B = 2.962, \varepsilon = 0.48598\right]$, $\left[R^B = 9.574, \varepsilon = -1.079\right]$, $\left[R^B = 89.138, \varepsilon = -2.0107\right]$, $\left[R^B = 4.9082, \varepsilon = 0.65233\right]$, $\left[R^B = -5.3926, \varepsilon = 1.2271\right]$.

Second, the payment scheme and group characterizations remain identical to those under competition for a given ε. This is because each type of firm's incentive to borrow from the bank or the big tech, and whether to default from the bank remain unchanged from the case when the big tech has no market power. Recalling that $p_b = \frac{R^B+1}{Y} + \varepsilon$, and $p_0 = \frac{1}{Y} + \varepsilon$, we present the following Lemma.

Lemma 2: *Given any $\varepsilon \geq \rho - 1$, and an R^B that satisfies the bank's break-even condition* (11), *types in Group 1, $p \leq p_0$, borrow form the bank and default strategically; (ii) types in Group 2, $p \in (p_0, p_b)$, borrow from the big tech and do not default strategically, while (iii) types in Group 3, $p \geq p_b$, borrow from the bank and do not default strategically.*

Third, an increase in ε results in an increase in R^B. This is because, given $\varepsilon \geq \rho - 1$, the bank's profit is increasing in R^B in a stable competitive equilibrium satisfying (11). Otherwise, a bank could decrease R^B, attract firms, and make a strictly positive profit. Thus, the break-even R^B must increase following an increase in ε since $\mathbb{E}\left(\Pi^B\right) < 0$ otherwise.

Fourth, the big tech may gain by increasing or decreasing ε from the level that solves $\mathbb{E}\left(\Pi^P\right) = 0$. We explain next. The big tech chooses ε to maximize its expected profit (12), such that (11) holds. We have $\frac{\partial \mathbb{E}\left(\Pi^P\right)}{\partial R^B} > 0$ since the net revenue is strictly positive for $p = \frac{R^B+1}{Y} + \varepsilon$. We also know from the third step above that an increase in ε will result in an increase in R^B. However, since $(Y(p-\varepsilon) - 1)$ decreases with ε, it is not obvious whether the big tech will gain by increasing or decreasing ε from the level that solves $\mathbb{E}\left(\Pi^P\right) = 0$.

Indeed, we show in an example, that the big tech optimally increases ε from the one that solves $\mathbb{E}\left(\Pi^P\right) = 0$ when the distribution of firm types is uniform. However, if the density function is altered in the example such that the the probability of a type decreases with type, the big tech optimally reduces ε from the level that solves $\mathbb{E}\left(\Pi^P\right) = 0$.

In the example below we rely on a common set of parameters: $1 = \alpha; \rho = 1.5, Y = 30; r = 1\%$. We take the density of the types p to be $f(p) = \gamma p^{\gamma-1}$. γ =1 corresponds to the uniform distribution, while with γ <1 the probability of a type decreases with p. We look for the values of R^B and ε that maximize $\mathbb{E}\left(\Pi^P\right)$ s.t. $\mathbb{E}\left(\Pi^B\right) = 0$. The minimum value that ε can take consistent with $\varepsilon \geq \rho - 1$ is 0.5.

Case $\gamma = 1$: the competitive equilibrium, that is the intersection of the expected zero profit function of bank and platform occurs for values of $R^B = 4.9082, \varepsilon = 0.65233$. At $\varepsilon = 0.5$ the corresponding value of R^B consistent with $\mathbb{E}\left(\Pi^B\right) = 0$ is $R^B = 3.0062$, which delivers $\mathbb{E}\left(\Pi^P\right) = -1.0816 \times 10^{-2}$. As in this case $\mathbb{E}\left(\Pi^P\right)$ increases with ε and R^B and it reaches its maximum value, $E\left(\Pi^P\right) = 2.1579 \times 10^{-2}$, for the maximum value of $\varepsilon = 0.654$ (and $R^B = 5.1154$) such that $\mathbb{E}\left(\Pi^B\right) = 0$ is upward sloping in the space R^B, ε. Thus the big tech chooses to increase ε w.r.t. the competitive equilibrium.

Case $\gamma = 0.9$: the intersection of the the expected zero profit function of bank and platform occurs for values of $R^B = 3.3369, \varepsilon = 0.50002$. The maximum values of ε and R^B such that $\mathbb{E}\left(\Pi^B\right) = 0$ is upward sloping in the space ε and R^B occur for $R^B = 4.2512, \varepsilon = 0.6$ with $\mathbb{E}\left(\Pi^P\right) = -0.02573$. Since in this case $E\left(\Pi^P\right)$ decreases with ε and R^B along the bank expected zero profit curve the big tech will increase its expected profit to $E\left(\Pi^P\right) = 1.4754 \times 10^{-5}$ by decreasing ε, s.t. $\varepsilon \geq \rho - 1$.

A.6 Big tech with restricted market share

Here we extend the model to the case in which the big tech can serve at most a "small" fraction $\alpha \in (0, 1)$ of randomly selected firms of each type p, while the bank serves a complementary fraction. We establish the following result:

Corollary 1. Under noisy and private type learning by the big tech, there exists both a $p_0 = \frac{1}{Y} + \rho - 1 \in (1/Y, 1/Y + \varepsilon)$, and a $p_b = \frac{R^B+1}{Y} + \varepsilon \in (\widehat{p}_b, 1)$ where $\widehat{p}_b = \frac{R^B+1}{Y} + \rho - 1$, such that firms choose to borrow from the bank or the big tech depending on their types as follows:

- Firms with $p \in [0, p_0)$, (Group 1) borrow from the bank.
- A randomly chosen fraction α of the firms with $p \in [p_0, p_b]$, (Group 2) borrow from the big tech at a signal-contingent rate (5) and do not default strategically. The complementary fraction of Group 2 borrow from the bank at the fixed break-even rate R^B, which is determined by the solution of expected profit condition of the bank and big tech ((14) and (15)) but only those with $p \in [\widehat{p}_b, p_b]$, do not default strategically.
- All firms with $p \in (p_b, 1]$, (Group 3) borrow from the bank at R^B and do not default strategically.

- In equilibrium $\varepsilon > \rho - 1$, where ε is determined by the zero expected profit conditions of the big tech and bank, (15) and (14).

Proof

The proof follows the same steps of that or Proposition 2. The difference will be that Group 2 is split between big tech and bank.

Group 1. Firms $p \in [0, \frac{1}{Y})$ are cutoff from the big tech. From (6) firms $p \in [\frac{1}{Y}, p_0)$ prefer to borrow from the bank and default strategically.

Group 2. For $p \in [p_0, \frac{1}{Y} + \varepsilon)$, the big tech's expected repayment is 0. Define a marginal type $p_b \geq \widehat{p}_b = \frac{R^B+1}{Y} + \rho - 1$ by (9) where the type p_b is indifferent between between borrowing from either lender with no strategic default as in (10). Recalling that firms with $p \in [\widehat{p}_b, 1]$ will repay both lenders after success, types $p \in [\frac{1}{Y} + \varepsilon, p_b)$ prefer to borrow from the big tech. A fraction α of them borrows from the big tech, and the complement from the bank. Thus for each $p \in [\frac{1}{Y} + \varepsilon, p_b)$, the expected repayment to the big tech is $\mathbb{E}\left[R(s)|p\right] = Y\left(p - \varepsilon\right) - 1$.

Group 3. From (10) firms with $p \in (p_b, 1]$ strictly prefer to borrow from the bank at R^B.

The bank repayment R^B, and the big tech noisy learning ε, are jointly determined by the zero expected profit conditions for the bank and the big tech, namely

$$\mathbb{E}\left(\Pi^B\right) = \underbrace{\int_{p_b}^{1} \left[pR^B - 1\right] f\left(p\right) dp}_{\text{Group 3}} + \underbrace{\left(1-\alpha\right)\left[\int_{\widehat{p}_b}^{p_b} pR^B f\left(p\right) dp - \int_{p_0}^{p_b} f\left(p\right) dp\right]}_{\text{Group 2}} - \underbrace{\int_{0}^{p_0} f\left(p\right) dp}_{\text{Group 1}} = 0, \tag{14}$$

and

$$\mathbb{E}\left(\Pi^P\right) = \underbrace{\frac{\alpha}{1 - F\left(1/Y\right)}\left[\int_{\frac{1}{Y}+\varepsilon}^{p_b} p\left(Y\left(p-\varepsilon\right) - 1\right) f\left(p\right) dp - \int_{p_0}^{p_b} \left(1+r\right) f\left(p\right) dp\right]}_{\text{Group 2}} = 0. \tag{15}$$

As in Proposition 2 $\varepsilon > \rho - 1$. This is because if $\varepsilon = \rho - 1$, in which case $p_b = \widehat{p}_B = \frac{R^B+1}{Y} + \rho - 1$, the solution for R^B generically would not satisfy (15) and (14). End of proof.

Finally, we analyze how regulations limiting the market share of the big tech impacts welfare. To do so we perform the comparative statics w.r.t. α of results in Corollary 1. We rely on the same set of assumptions of the other calibrations in this appendix, namely $\rho = 1.5, Y = 30; r = 1\%$ and density $f(p) = \gamma p^{\gamma - 1}$. With uniform distribution $(\gamma = 1)$ as α decreases from 1, ε increases, and p_b increases. Since p_b increases, more firms that borrow from the bank (Group 2) strategically default. It means that placing regulatory caps to the big tech market share has welfare costs. With $\gamma = 0.9$ as α decreases from 1, p_b increases as well while the impact on ε is not monotonic.

Previous volumes in this series

All volumes are available on our website www.bis.org.