THE ROLE OF FINTECH IN MITIGATING INFORMATION FRICTION IN SUPPLY CHAIN FINANCE

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CONTENTS

FIGURES

ABSTRACT

Micro, small, and medium-sized enterprises in developing countries face severe financing difficulties, especially when trying to expand internationally. “Information friction” is a significant cause of this financing gap. Recent financial technologies (fintech) can improve supply chain finance efficiency. This paper therefore proposes a conceptual and analytical framework to study how fintech can close the financing gap by reducing information friction. We classify fintech into two categories: information processing technology (Type-A) and information collecting technology (Type-B) and find that both help close the financing gap by lowering the probability of misclassification of good firms as bad. Banks’ optimal Type-A investment increases in the bank’s size, profit margin, and the fraction of good firms in the market. They invest in Type-B if and only if the investment is sufficiently small. Due to “double marginalization,” a bank’s optimal fintech investment is lower than a socially optimal level, calling for mechanisms to incentivize or complement banks’ investment in fintech.

Keywords: artificial intelligence, digitization, fintech, information friction, supply chain finance

JEL codes: O14, O24, O31

I. INTRODUCTION

Micro, small, and medium-sized enterprises (MSMEs) in developing countries rely on external finance to sustain operations and grow domestically and internationally. However, these enterprises commonly face significant challenges in gaining access to finance, particularly under the "open account" trade finance terms common in the competitive environment now prevalent between importing developed countries and exporting firms in developing countries.

This paper therefore examines emerging financial technologies (fintech) in information processing and information collecting—particularly through digitization and automation, biometrics and identity management, and blockchain—that hold promise for widening access to finance among such enterprises.

Firms commonly use three trade finance modes: cash-in-advance, letters of credit, and open account (see Antràs and Foley 2015; Foley, Johnson, and Lane 2010; Schmidt-Eisenlohr 2013). The latter, open account (trade credit) terms, are popular in trades between importers in the developed world and exporters from the emerging markets, where payment risk is in general low, but performance risk can be high (the risk that exporters may fail to deliver). This is because such terms allow importers to pay exporters a certain time after receipt of the goods, thus imposing high importer repayment risk on exporters. The flexibility this gives importers to resell the goods before paying exporters is behind the prevalence of open account in the competitive conditions in current global business environments (Foley, Johnson, and Lane 2010). Such terms protect importers from the exporter's performance risk.

By contrast, cash-in-advance trade finance terms require importers to pay exporters before they ship the goods, thus imposing the need to secure finance on importers. And letter-of-credit terms require banks to commit payments before exporters produce the goods and to pay the exporters upon shipping, thus eliminating the risk that exporters will not receive payment.

Despite their advantages and popularity compared to cash-in-advance and letters of credit, however, open accounts inevitably aggravate the already challenging financial situations in developing countries that MSMEs face.

Financial institutions and national, regional, and international organizations have introduced various open account-based trade finance products and programs, also commonly known as supply chain finance.[1] Among them, purchase order and receivable finance have received growing attention, especially for financially constrained exporters without collateral. But MSMEs still face challenges accessing finance. According to the Asian Development Bank's (ADB) 2017 Trade Finance Gaps, Growth, and Jobs Survey (Di Caprio, Kim, and Beck 2017), the Asia and Pacific region contributed about 46% of worldwide proposals for trade finance (firm requests to banks) and about 39% of proposal rejections, in which MSMEs and mid-cap firms account for 74% of these rejections. This wide financing gap hurts growth in such firms, and thus hinders their job creation. Once a loan application is rejected, about 60% of responding firms in the survey reported that they failed to execute contracts, which leads to significant losses in trade. Moreover, the survey points out that 36% of these trade finance rejections could have been funded.

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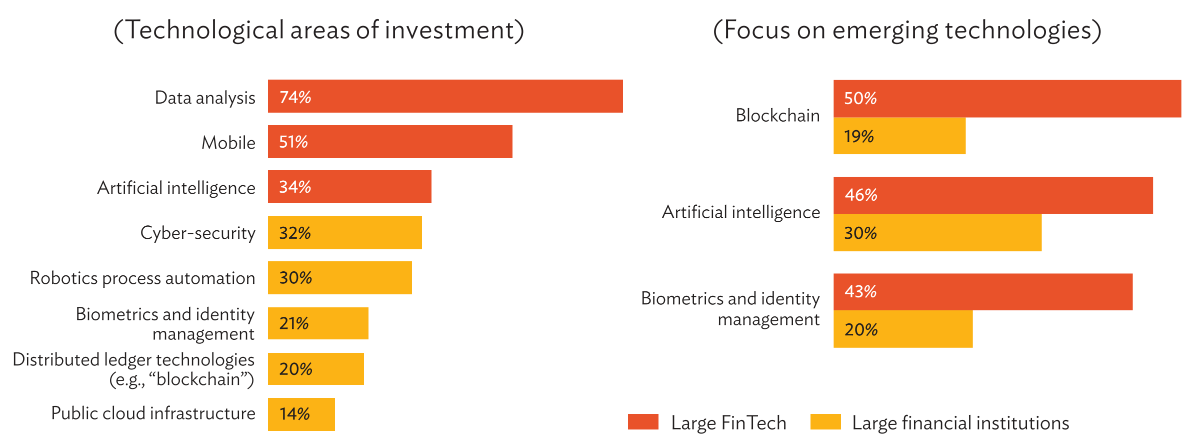
1 The paper refers to supply chain finance as any form of financial product and solution that leverages information from the extended supply chain, and, hence, covers both domestic and international transactions. As it is easier for banks to retrieve funds in domestic transactions, our focus is on international transactions.

Banks reject trade finance applications for many reasons, and some give rise to the existence of "information friction."[2] For example, banks rejected about 29% of proposals because they failed to meet know-your-customer regulations. Banks nowadays face great pressure to comply with these regulations and exert considerable effort doing so. In one notorious example of failure on this front, The Hongkong and Shanghai Banking Corporation (HSBC) in late 2012 was forced to pay just over $1.9 billion in fines for allowing itself to become a money launderer, particularly involving illegal drug money flowing out of Mexico (Viswanatha and Wolf 2012). However, because MSMEs are small, they struggle to complete the complicated and time-consuming process, which prohibits banks from initiating relationships and resulting in significant information friction during loan approval. Moreover, 21% of rejections are related to insufficient collateral or information.

However, financial institutions may benefit from technology advances that allow faster and more efficient responses, particular as related to digitization. Indeed, about 80% of responding banks in the ADB survey expected lower loan approval costs arising from digital technologies, including facilitating know-your-customer checks, reducing the costs of due diligence, and enhancing ability to assess the risks of small clients.

Interestingly, in the same survey, digitization initiatives alone do not seem to reduce rejection rates for small firms, reflecting the challenge banks face in reducing information friction. Although digitization does facilitate loan process efficiency and is the first step for adopting other advanced technologies, it alone does not help collect more useful data nor enable better information processing in banks. In addition to digitization, banks are searching for fintech tools that enable them to extract more and better information. A PricewaterhouseCoopers report on global fintech investment (see an extraction from the report in Figure 1) reveals a strong focus on information.

Figure 1: Investment in Technology



Note: These two images are extracted from PricewaterhouseCoopers Global FinTech Report 2017. The image on the left shows response of firms to the question "*What are the most relevant technologies for your business that you plan to invest in within the next 12 months?*," while the one on the right shows the percentage of large companies (more than 500 employees) that identified these emerging technologies as the most relevant to invest in within the next 12 months.
Sources: PricewaterhouseCoopers Global FinTech Report 2017.

[2] Information friction refers to incentive misalignment caused by information asymmetry between involved parties.

This paper therefore focuses on fintech that help alleviate information friction. Depending on the specific role such technologies play, we classify these technologies into two categories: information processing technology and information collecting technology.

Information processing technologies convert the vast amounts of raw data banks own (or could obtain) into useful information in lending decisions. Leveraging digitization, banks now have enormous amounts of data ready to be analyzed. Financial institutions have started to adopt advanced analytics and artificial intelligence (AI). According to the business magazine *Forbes*, analysts estimate that AI will save the banking industry more than $1 trillion by 2030 (Maskey 2018). For example, Citibank is using machine learning and big data in its antimoney-laundering structure to prevent fraud.

Information collection technologies, meanwhile, collect additional new data, such as through digitization and automation, biometrics and identity management, and blockchain. For example, using a new technology, COiN, JPMorgan Chase dramatically reduces the time needed to review documents and extract data; where 12,000 documents originally required more than 360,000 hours of work, it now needs only seconds (Maskey 2018).

Biometrics and identity management enable banks to recognize MSMEs and link their business history with their current status faster and more efficiently. Moreover, by establishing a standard in firm identity, banks (and all stakeholders along supply chains) can accurately link information from various channels, such as ports, airports, and customs (e.g., a vessel sailing to Singapore port containing shipments to Carrefour, a big supermarket chain in Singapore).

Finally, large financial institutions are starting to invest in blockchain to enhance digitization and to collect additional information with superior accuracy and transparency. Jointly with Reliance Industries and Tricon Energy, HSBC and ING banks have adopted blockchain in their trade finance transactions (HSBC 2018). The use of blockchain "has a transformative impact on trade finance transactions and enables greater transparency and enhanced security in addition to making it simpler and faster," notes Ajay Sharma, Regional Head of Global Trade and Receivables Finance of Asia Pacific for HSBC.

European banks are also collaborating in developing their own open account trade finance using blockchain technology (we.trade) to "make financing simpler, cheaper, and faster" (Morris 2018, Wass 2019). Finally, information collection technologies are also related to recent efforts to promote digital standards, legal entity identifiers, and legislation related to digitalizing trade documents, as they enable more efficient collection of information through multiple sources.

Although these technologies all aim for collecting more information, the nature of the new information may differ. Specifically, applications using blockchain, such as we.trade and IBM Maersk, connect ports, customs, logistics companies, and even some airlines to collect the status of transactions. In addition to blockchain, other applications have leveraged traditional platforms to collect more data. For example, GT Nexus (rebranded to Infor Nexus in 2019) collects supply chain information from suppliers, manufacturers, brokers, third-party logistics providers, and banks, among others. Such a service allows firms in the supply chain to know the status of transactions, including but not limited to the location of goods, custom status, payment status, etc. These additional data can be directly used in a bank's lending decisions without the need to be further processed.

However, some platforms collect information that may need to be further processed and hence, a firm's capability in processing information highly influences whether this type of information can be efficiently used. For example, a Taobao or TMall (subsidiaries of Alibaba group) seller can initiate a loan request through MyBank.cn (a subsidiary of Ant Financial Services Group), which will in turn collect this seller's business history from Taobao or TMall, and then process this information before making a lending decision. Another example is the fintech lender Kabbage, which provides a rapid lending product for small business in the United States (US) and the United Kingdom by assessing the risk of small business using the business borrowers' operational and financial data, including Amazon and eBay trade information, PayPal transactions, and UPS shipment volume, and so on.[3] In this case, Kabbage utilizes both information collection technology (through interface with other companies enabled by technology) and information processing technology (processing a large amount of transactional data to make the lending decision). Later, we will illustrate how information processing technologies and information collection technologies interact with each other by considering whether new information can be directly used or not.

Technological advancements in this area benefit MSMEs especially by responding to their financing needs more efficiently at lower cost. Yet, the role of different types of fintech tools in facilitating trade is still underexplored in such a context. With a focus on how fintech can help enhance access to trade finance for MSMEs, we study how trade finance products can help reduce unmet demand for trade finance by taking advantage of technology.

In this paper, we focus on supply chain finance products that are based on open account (trade credit), particular finance of receivables and purchase order finance. Manova (2012) shows how financial market imperfections distort international trade, and such financial friction is more profound for financially constrained exporters than domestic producers for higher working capital needs due to longer shipping times. To reduce financing gaps, an intuitive approach is to facilitate trade finance for the 36% of rejected trade finance transactions mentioned in the ADB 2017 survey, which, as noted, could have been funded if banks had more information. Thus, we focus on exporters' need for finance before importers pay their bills. Moreover, financially unconstrained firms may raise finance using their collateral, and hence may be less likely to be in these 36% rejected transactions. As such, the paper tackles only the situation for exporters equipped with purchase orders or receivables.

In the paper's two categories—information processing and information collecting technologies—the former (here called Type-A) includes data analytics and AI and allows financial institutions to better process raw data and transform them into useful information that can directly guide decision-making. The latter (Type-B), includes blockchain, biometrics and identity management, and digitization, and allows more data and information to be collected in decision-making.[4] We find that both types help close financing gaps by offering a more accurate signal to identify the good firms that deserve loans.

Next, we study a bank's investment decisions and find that its Type-A investment increases in bank size, profit margin, and fraction of good firms in the market. The two types of fintech can

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[3] A customer needs to provide the log-in information to Kabbage to receive a loan approval for up to $250,000. See https://www.kabbage.com/how-it-works/qualifying/ for more information.

[4] For blockchain and biometrics, they also strengthen data security, which may not function in the same way as digitization works. As in this paper, we focus on information friction, we only consider their ability to collect information that will otherwise be discarded due to the possibility of falsification (e.g., falsification on International Standards Organization (ISO) 90001 and/or ISO 14001 certifications and accounting frauds).

complement or substitute and their relationship depends on whether the Type-B investment can further lower the financing gap or not. Banks invest in Type-B if and only if the investment in Type-A is sufficiently small. Finally, we investigate the gap between banks' optimum and social welfare optimum. Due to the "double marginalization" between the bank and the borrower, the bank's optimal fintech investment level is lower than the socially optimal level.[5] This calls for mechanisms supported by the public sector—including governments and international organizations such as the International Standards Organization (ISO), the World Customs Organization, and International Chamber of Commerce—that incentivize or complement banks' investment in fintech. In particular, public sectors can support mechanisms to lower the cost of technology adoption, making it easier and cheaper for banks. Such mechanisms include, but are not limited to, developing digital standards and ecosystems to reduce entry barriers for technology adoption, establishing legal entity identifiers to reduce the time and effort to match real-time information about exporters for banks, and implementing rules and legislation for digital trade to lower banks' legal risks for adopting new technologies.

In the rest of the paper, section II summarizes related literature and section III introduces a parsimonious model that captures the trade financing gap and the role of fintech. Sections IV and V assess how fintech can help in closing the trade financing gap. The bank's investment in fintech is discussed in section VI. We conclude the paper in section VII.

II. LITERATURE REVIEW

The paper is related to three streams of literature: trade finance, supply chain finance, and fintech. The traditional trade finance literature focuses on the interaction between importers or exporters and banks, its discussion mostly surrounding the choice between cash-in-advance, open account, and letter-of-credit terms. Antràs and Foley (2015) study how each of these supports international trade. In similar fashion, we also consider importers' repayment risks as well as exporters' quality risks. And in a similar setup, Schmidt-Eisenlohr (2013) considers a profit maximization problem for exporters and discusses how to choose a take-it-or-leave-it contract to importers by taking financing costs as well as importer repayment risks into account. Extending the model of Schmidt-Eisenlohr (2013), Hoefele, Schmidt-Eisenlohr, and Yu (2016) use the data from the World Bank Enterprise Survey to show that country characteristics significantly influence exporters' payment contract choices. We differentiate our work from this stream of literature by focusing on how technology can mitigate the negative impact from information friction.

In addition to the above papers that use game-theoretic models to understand trade credit behavior, Niepmann and Schmidt-Eisenlohr (2017a) use data provided by the Society for Worldwide Interbank Financial Telecommunications (SWIFT) and find that US exporters rely more on letters of credit and documentary collections, instead of open account and cash-in-advance terms. Also focusing on letter of credit terms, Niepmann and Schmidt-Eisenlohr (2017b) show that a negative shock to a country's letter-of-credit supply significantly reduces US exports to that country.

5 Double marginalization is a common phenomenon in supply chains, where two parties at different vertical levels exercise their market powers to set their prices above their respective marginal costs, leading to welfare loss. In this paper, the bank charges the exporter firm above its marginal cost, and then the exporter firm charges its importer customer above its marginal cost.

More recently, motivated by the fast growth of open account-based trade finance, also commonly known as supply chain finance, academics in both finance and management examine various financial programs and products within supply chain finance. As the basis of supply chain finance, open accounts, also known as trade credit, have received significant academic attention. The main focus is to explain why sellers provide financing to their customers in the presence of specialized financial institutions. Theoretical and empirical research allude to the fact that trade credit plays important financial and operational roles, such as alleviating information asymmetry (Biais and Gollier 1997), mitigating moral hazard (Burkart and Ellingsen 2004), and sharing demand risk (Yang and Birge 2018).[6]

Despite its various advantages, trade credit inevitably increases the supplier's financial burden. Consequently, other supply chain finance products and solutions are invented. Receivable finance is the most commonly used, such as factoring (Klapper 2006), reverse factoring, or dynamic discounting (Hu, Qian, and Yang 2018). Such products rely on completed transactions between the buyer and seller. Another related product is trade credit insurance (Yang, Bakshi, and Chen 2019), which insures the supplier against the buyer's payment default risk, allowing suppliers to borrow at a lower rate from banks using their account receivables.

Despite their prevalence, receivables finance is often not sufficient to meet MSMEs' financing needs, especially for those looking to grow. More recently, academics have started to examine supply chain financing mechanisms that do not rely on completed transactions. Among them, Tang, Yang, and Wu (2018) compare purchase order finance with buyer direct finance, in which buyers directly offer finance as well as sourcing contracts to suppliers and, hence, the buyers bear the responsibility of screening and evaluating the exporters. Incorporating the repayment risks and exporter (supplier) performance risk, they discuss how information distortion affects contract efficiency. On the other hand, Reindorp, Tanrisever, and Lange (2018) consider different types of information issues about supplier demands and production capabilities, and study how a minimum purchase order quantity committed by buyers can mitigate information asymmetry issues.

In the case when the MSMEs are the buyers in a supply chain, in addition to trade credit, large sellers also provide financial assistance to these small buyers by orchestrating joint finance programs in collaboration with banks. Such joint finance programs are also known as distributor finance. Zhang, Huang, and Yang (2019) find that these programs can help in closing MSMEs' financing gap by allowing them to have access to large banks with more sophisticated risk management practices, as well as pooling idiosyncratic risks among MSMEs.

In our paper, we focus on the interaction between banks and exporters through purchase order and receivable finance and discuss how fintech adoption can help resolve information friction. Compared to the aforementioned papers in the supply chain finance literature, which often focuses on the relationship between importers (buyers) and exporters (suppliers), instead of banks and the two parties, our paper focuses on how fintech enables banks to make better lending and investment decisions.

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[6] We refer readers to Lee, Zhou, and Wang (2018) and Chod, Lyandres, and Yang (2019) for recent summaries of the trade credit literature.

Finally, the recent emergence of fintech has attracted the attention not only of practitioners, but also academics. Stringent regulations and compliances, strong competition from new entrants, and rising costs push financial industries to embrace new fintech. Philippon (2015) points out the inefficiency in US financial intermediation (the unit cost has remained around 2% for the past 130 years). To stay competitive, financial institutions have started to innovate; examples include digitization and automation in payment, trading, and customer services, blockchain, AI, and machine learning, cryptocurrencies, peer-to-peer lending and crowdfunding. Although regulations and policy may still need to be optimized (Philippon 2016), the fintech movement does create opportunities and competition for financial institutions. The adoption of blockchain by HSBC and ING and AI-enabled process improvement by Citibank and JPMorgan Chase are great examples of how banks take advantage of opportunities. However, Buchak et al. (2018) also show how fintech and regulation arbitrage contribute to the growth of shadow banks, (online) nonbank lenders falling outside the scope of traditional banking regulation. Lee et al. (2019) show that in a trade finance process that involves multiple milestones, by acquiring and verifying real-time information on whether the order has achieved certain milestones through blockchain or other information technologies, the financial institution that finances this trade transaction is able to lower its regulatory capital requirement, and thus lowers the financing cost borne by the exporter. In our paper, we identify the value of fintech tools through information friction reduction and consider how policy makers and governments can promote adoption of these fintech tools.

III. MODEL SETUP

Consider a bank facing a group of N homogenous MSME business borrowers without any initial endowment.[7] Each supplier submits a loan proposal of borrowing c from the bank. Here, N represents the size of the bank. The bank is willing to finance a proposal as long as the loan term can generate its required return $r \geq r_0$, in which r_0 represents the bank's cost of borrowing. We let $R = (1 + r)$ and $R_0 = (1 + r_0)$. Thus, $R - R_0$ represents the bank's profit margin, and it captures the competitiveness of the banking sector. In the extreme case that the banking sector is perfectly competitive, r equals r_0, and the bank simply breaks even.

Our model applies to both the purchase order financing setting and receivable financing (e.g., factoring and reverse factoring) setting. Under the purchase order financing setting, the supplier has secured a purchasing order from an overseas buyer to produce a single unit of goods. Knowing that the supplier is unreliable, the buyer only pays the supplier when the goods are delivered. Specifically, we assume that the buyer will pay the supplier a wholesale price w if the order is successfully delivered. Thus, the supplier needs to finance the entire production cost c through the bank under purchase order financing. The interpretation under the receivables financing setting is similar. In the following, we will focus on the purchase order financing setting to avoid repetition.

To focus on the role of fintech in reducing information friction, we focus on information asymmetry as the sole form of financial market friction. We capture information asymmetry using the uncertainty of the supplier's future cash flow. The repayment of the loan depends on the probability that the supplier will be paid by the buyer, which in turn depends on the supplier's operational capability. Specifically, we assume there are two types of suppliers: capable (good, H for high type) and

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[7] In principle, our model applies to both MSME borrowers and large business borrowers. However, it is mainly focused on MSMEs, as large firms would normally have other means to obtain financing, for example, by using collaterals or through public markets. As a result, we assume limited liability in this paper.

incapable (bad, L for low type), each with their own distribution of future payoff, Π_i and the cumulative distribution function and probability density function of Π_i are F_i and f_i, respectively. It is intuitive that we assume that F_H stochastically dominates F_L. Further, let there be a fraction of $\lambda \in (0,1)$ capable suppliers in the market. An alternative interpretation of the model is that a specific supplier is good at certain orders but not others. An operational interpretation of the binary distribution is yield uncertainty.

To avoid the trivial case that no firm is worth financing, we make the following assumption:

$$E[\Pi_H] > Rc > E[\Pi_L] \tag{1}$$

In addition, we assume that it is not efficient to finance the average firm without fintech, or alternatively, the bank will not finance all loan applications as it is not profitable in expectation. That is,

$$\lambda E[\Pi_H] + (1-\lambda)E[\Pi_L] < Rc \tag{2}$$

This captures the fact that there is a financing gap defined as the fraction of firms that should have received financing but failed to do so.

For tractability, we assume that the good supplier will successfully execute the order (and hence get paid) with probability 1, while the probability that the bad supplier will be able to deliver the product is p. Under this simplifying assumption, Π_H equals to w with probability 1, and Π_L follows a binary distribution that equals w with probability p, and 0 with probability $1-p$. Therefore, the above assumptions (1) and (2) can be rewritten as:

$$w > Rc > [\lambda + (1-\lambda)p]w \tag{3}$$

To capture information asymmetry on the supplier's type, we assume that the supplier knows its type, but the bank only receives certain related information, based on what the bank will use to form a signal. We note that as the supplier has no assets, the bank cannot offer a screening contract to determine the supplier's type.

We assume there are two sources of information that the bank can use to form valuable signals about the supplier. One is tamper free (e.g., public information), and the other is subject to the supplier's strategic manipulation (e.g., a certificate or qualification that the supplier may counterfeit). Each source of information will lead to a binary signal: 0 means that the firm is bad, and 1 that the firm is good. And the bank then uses these two signals jointly to determine the type of the supplier.

The role of fintech in our model is to improve the accuracy of the signal(s).

1. Information processing technology (Type-A). Given the availability (and the authenticity) of the information, analytics improves the accuracy of the signals of all available information. We capture a bank's Type-A investment using a continuous decision variable $A > 0$, which can be interpreted as the amount of resource the bank invests in Type-A technologies, such as number of analysts, information technology equipment, etc.
2. Information collecting technology (Type-B). Type-B technology, such as blockchain, biometrics, and digitization, makes second source information available to the bank. Type-A technology can also increase the accuracy of the signal based on this information source.

We capture a bank's Type-B investment as a binary decision. We note that although a bank can adopt a subscription term to use blockchain, biometrics, or digitization service from a platform, the initial investment in technology adoption often involves revamping entire information systems and training programs, etc. Therefore, this assumption of a binary decision is especially relevant in the beginning of technology adoption process. The bank either invests in Type-B technology at cost B, or does not invest.

To incorporate multiple signals, we consider a model similar to Biais and Gollier (1997). The difference is that the additional information available from the seller is conveyed to the bank in the form of trade credit, so it is a signaling game. In our case, we can say that Type-B technology issues the authenticity of some additional information which cannot be used previously due to quality issues. So, the bank may use the adoption of Type-B technology as a screening mechanism. The role of Type-A technology is still to improve how information can be transformed into a useful signal. The substitutability or complementarity of Type-A and Type-B technologies depend on how information conveyed in Type-B technology is processed in generating a useful signal, which we will discuss in detail later.

For tractability, we assume that there is only one type of misclassification risk: when the firm is good, it may be misclassified as bad. Therefore, we capture the quality of the signal of the public information (θ) by this misclassification risk μ; that is, when the supplier is good, the probability that the signal (the outcome from the classifier) is negative ($\theta = 0$) be :

$$\Pr(\theta = 0|good) = \mu \tag{4}$$

On the other hand, when the supplier is bad, it cannot be misclassified as good. That is:

$$\Pr(\theta = 1|bad) = 0 \tag{5}$$

Both the signal θ and the misclassification risk μ are functions of the fintech investment. Specifically, let A represent the Type-A investment level, and the function μ is parameterized by A. Intuitively, μ is convexly decreasing in A, that is:

$$\frac{\partial \mu}{\partial A} < 0; \frac{\partial^2 \mu}{\partial A^2} > 0 \tag{6}$$

For a microfoundation of the model, let A capture the number of classifiers the bank can implement. For example, the performance of different classifiers follows a certain distribution, and we will take the maximum of that, so the accuracy improvement will be concavely increasing in A. $\mu(A = 0)$ captures the baseline accuracy of the signal, that is, the status quo without any fintech investments. It serves as a proxy for the size of the borrower: $\mu(0)$ is higher for large and established borrowers, while lower for small borrowers without an established track record.

The information gained from Type-B technology works similarly; the bank also assesses this second source of information, which is used to generate a signal. Let the signal of the Type-B information be θ_B, and let the corresponding misspecification risk be μ_B, which is also influenced by the Type-A investment A:

$$\frac{\partial \mu_B}{\partial A} \leq 0; \frac{\partial^2 \mu_B}{\partial A^2} \geq 0 \tag{7}$$

Without loss of generality, similar to Biais and Gollier (1997), we assume that θ and θ_B are independent, that is,

$$\Pr(\theta = 1|\theta_B) = \Pr(\theta = 1) \tag{8}$$

Finally, in the following analysis, while deriving general results under these general technical assumptions, to better illustrate and to obtain additional insights, we impose a specific functional form on how the two types of fintech improve signal quality. Specifically, we examine an exponential functional form:

$$\mu = ke^{-tA}; \mu_B = k_B e^{-t_B A} \tag{9}$$

Here k and k_B capture the base quality of the signal, while t and t_B capture how sensitive the quality of the signals is to the Type-A investment. Based on this specification, it is easy to see that k and k_B and t and t_B correspond to the case where the information is straightforward. That is, the raw data itself can lead to a high-quality signal without much additional processing. On the other hand, when both k and k_B, as well as t and t_B, are high, the data is *complicated* and investment in Type-A technology is crucial in transforming them into useful information. We also provide a polynomial special form in Appendix 1 for robustness checks.

IV. CLOSING MSMES' FINANCING GAP THROUGH FINTECH

Under the model proposed in the previous section, this section focuses on examining the impact of given levels of fintech investment on the financing gap, which we define as the fraction of firms who should receive financing but failed to do so. We first consider the case without the Type-B investment, and then the one with; in both cases, we consider the Type-A investment, but it can be zero if it is optimal to do so for the bank.

A. The Case without Type-B Technology

In the case without Type-B technology, based on the above model setting, we use the Bayes' rule to calculate the probability that the supplier is good conditionally on the (nonblockchain) signal being good ($\theta = 1$), which is

$$\Pr(good|\theta = 1) = 1 \tag{10}$$

Thus, when the observed signal is good, the bank does not face any risk. Denote the interest rate that the bank charges the supplier as r_b, which is a function of θ. Following the same notation as R, we denote $R_b = 1 + r_b$. Thus, we obtain that $R_b(\theta = 1) = R$. Correspondingly, the bank's profit is:

$$\pi_b(\theta = 1) = N(R - R_0)\Pr(\theta = 1)\,c = N(R - R_0)c\lambda(1 - \mu) \tag{11}$$

Clearly, the bank's profit decreases in μ.

On the other hand, when $\theta = 0$, based on the above assumptions, we know the probability that this supplier is good is,

$$\Pr(good|\theta = 0) = \frac{\lambda\mu}{\lambda\mu + (1 - \lambda)} \tag{12}$$

For the bank to lend at $\theta = 0$, the interest rate R needs to be set to be $R_B(\theta = 0)$, which must satisfy,

$$R_b c \frac{\lambda\mu}{\lambda\mu + (1-\lambda)} + R_b c p \frac{1-\lambda}{\lambda\mu + (1-\lambda)} = Rc \tag{13}$$

Thus, we derive the interest rate to the supplier, that is,

$$R_b = \left[1 + \frac{(1-\lambda)(1-p)}{\lambda\mu + (1-\lambda)p}\right] R \tag{14}$$

As shown, the risk premium decreases in μ. This is because when μ is high, the $\theta = 0$ mix has a large fraction of good firms.

For this interest rate to be acceptable to the supplier, we must have the wholesale price w be larger than the cost of this transaction, $R_b c$, which is denoted as $\underline{w}$. That is:

$$w \geq \underline{w} = R_b c = \left[1 + \frac{(1-\lambda)(1-p)}{\lambda\mu + (1-\lambda)p}\right] Rc \tag{15}$$

Under a parametric assumption, $\lambda \neq 0$, $\underline{w}$ decreases in μ. When $\mu = 0$, that is, no misclassification, we have,

$$\underline{w} = \frac{1}{p} Rc \tag{16}$$

And when $\mu = 1$ (which can be used to approximate the case without no information), we have,

$$\underline{w} = \frac{1}{\lambda + (1-\lambda)p} Rc \tag{17}$$

Depending on the range of w, $\underline{w}$ may be greater than the highest possible w. In this case, the bank will never lend if the signal is bad ($\theta = 0$).

Proposition 1. *When $[\lambda + (1-\lambda)p]w \leq Rc$, without Type-B technology, the bank only finances the firm when the signal is good ($\theta = 1$).*

In the following analysis, we assume that the condition $[\lambda + (1-\lambda)p]w \leq Rc$ is satisfied and hence the above proposition holds. Thus, the financing gap G, as defined as the fraction of firms who should have received financing but could not, follows:

$$G = \lambda\mu \tag{18}$$

Proposition 2. *Without Type-B technology,*

1. *the financing gap G decreases convexly in Type-A investment A, and*
2. *the impact of A on G is higher when a greater fraction of firms is good (large λ).*

B. The Case with Type-B Technology

In this case, we have two signals: θ and θ_B, where the latter one is from Type-B technology. The definition is similar to the ones without Type-B technology, that is, when the supplier is good, we have:

$$\Pr(\theta_B = 0|good) = \mu_B \tag{19}$$

On the other hand, when the supplier is bad, it cannot be misclassified as good, that is,

$$\Pr(\theta_B = 1|bad) = 0 \tag{20}$$

Under this case, we consider four scenarios depending on θ_B and θ:

$$\Pr(good|\theta = 1, \theta_B = 1) = \frac{\Pr(good, \theta = 1, \theta_B = 1)}{\Pr(\theta = 1, \theta_B = 1)} \tag{21}$$

$$= \frac{\Pr(\theta = 1|good)\Pr(\theta_B = 1|good)\Pr(good)}{\Pr(\theta = 1, \theta_B = 1)} = 1 \tag{22}$$

Similarly, $\Pr(good|\theta = 1, \theta_B = 0) = \Pr(good\ |\theta = 0, \theta_B = 1) = 1$. Finally,

$$\Pr(good|\theta = 0, \theta_B = 0) = \frac{\Pr(good, \theta = 0, \theta_B = 0)}{\Pr(\theta = 0, \theta_B = 0)} = \frac{\lambda\mu\mu_B}{\lambda\mu\mu_B + (1-\lambda)} \tag{23}$$

Proposition 3. *When $[\lambda + (1-\lambda)p]w \leq Rc$, with Type-B technology, the bank finances the firm if and only if at least one of the two signals is good ($\theta + \theta_B \geq 1$).*

Combined, the fraction of firms that can secure financing is:

$$1 - \Pr(\theta = 0, \theta_B = 0) = \lambda(1 - \mu\mu_B) \tag{24}$$

And the financing gap with Type-B technology, which is denoted as G_B, then becomes:

$$G_B = \lambda\mu\mu_B \tag{25}$$

Taking derivatives, we have,

$$\frac{\partial G_B}{\partial A} = \lambda\mu\frac{\partial \mu_B}{\partial A} + \lambda\mu_B\frac{\partial \mu}{\partial A} < 0 \tag{26}$$

Clearly, the Type-A investment still closes the financing gap. Further,

$$\frac{\partial^2 G_B}{\partial A^2} = \frac{\partial}{\partial A}\left(\lambda\mu\frac{\partial \mu_B}{\partial A} + \lambda\mu_B\frac{\partial \mu}{\partial A}\right) = \lambda\left\{2\frac{\partial \mu}{\partial A}\frac{\partial \mu_B}{\partial A} + \mu\frac{\partial^2 \mu_B}{\partial A^2} + \mu_B\frac{\partial^2 \mu}{\partial A^2}\right\} > 0 \tag{27}$$

Proposition 4. *With Type-B technology,*

1. *the financing gap G decreases convexly in the Type-A investment A, and*
2. *the impact of A on the financing gap G is higher when a greater fraction of firms is good (greater λ).*

V. RELATIONSHIP BETWEEN TYPE-A AND TYPE-B TECHNOLOGIES

Next, we consider the substitutability and complementarity between these two types of fintech. To do that, we compare $\partial G_B/\partial A$ and $\partial G/\partial A$:

$$\frac{\partial G_B}{\partial A}-\frac{\partial G}{\partial A}=\lambda\mu\frac{\partial \mu_B}{\partial A}+\lambda\mu_B\frac{\partial \mu}{\partial A}-\lambda\frac{\partial \mu}{\partial A}=\lambda\left[\mu\frac{\partial \mu_B}{\partial A}-(1-\mu_B)\frac{\partial \mu}{\partial A}\right] \tag{28}$$

Proposition 5. *The Type-A and Type-B technologies are complementary if and only if:*

$$\frac{\mu}{1-\mu_B}>\frac{\frac{\partial \mu}{\partial A}}{\frac{\partial \mu_B}{\partial A}} \tag{29}$$

As *A* increases, the left-hand side decreases. Thus, Type-A and Type-B technologies are more likely to be complementary when *A* is small and are substitutable when *A* is large. Using this proposition, we can further identify sufficient conditions for the two investments to be substitutable in the next corollary.

Corollary 1. *The Type-A and Type-B investment is substitutable if*

1. $\mu+\mu_B\leq 1$ *and* $\frac{\partial \mu}{\partial A}\leq\frac{\partial \mu_B}{\partial A}$ *for all* $A\geq 0$*, or*
2. $\frac{\partial \mu_B}{\partial A}=0$.

The second condition suggests that when the Type-A investment does not help improve the information collected by Type-B technology, that is, the information collected through Type-B fintech is straightforward, the two types of fintech are substitutable. This is intuitive: as additional information is collected, the overall signal quality improves; thus, the marginal benefit of improving the signal based on part of the information is reduced. For example, the additional information is a bit of tamper-free evidence of the supplier's qualification.

Symmetrically, we have the following condition under which the two types of fintech are complementary.

Corollary 2. *The Type-A and Type-B investment is complementary if* $\frac{\partial \mu_B}{\partial A}\gg\frac{\partial \mu}{\partial A}$.

This scenario applies when the newly collected information requires more processing than the original information; for example, if the bank used to rely on a traditional credit score to make a lending decision, and this credit score can be used directly without further process (by Type-A fintech). Now, with Type-B fintech, the bank is able, through a digital payment system such as PayPal and AliPay, to collect a large number of payments made to the borrower. While this information is valuable, it cannot be used immediately without being analyzed by advanced analytics. In this case, the two types of fintech are clearly complementary.

To numerically illustrate the relationship between Type-A and Type-B technologies, we apply the following parameter sets in the exponential form as characterized in equation (9) to form two special cases.

1. Straightforward information that we can directly use in a transaction regardless of the bank's Type-A investment (e.g., whether a delivery has passed inspection or customs).
2. Complicated information that may require further processing by Type-A technology (e.g., new sources of historical payments and performance data).

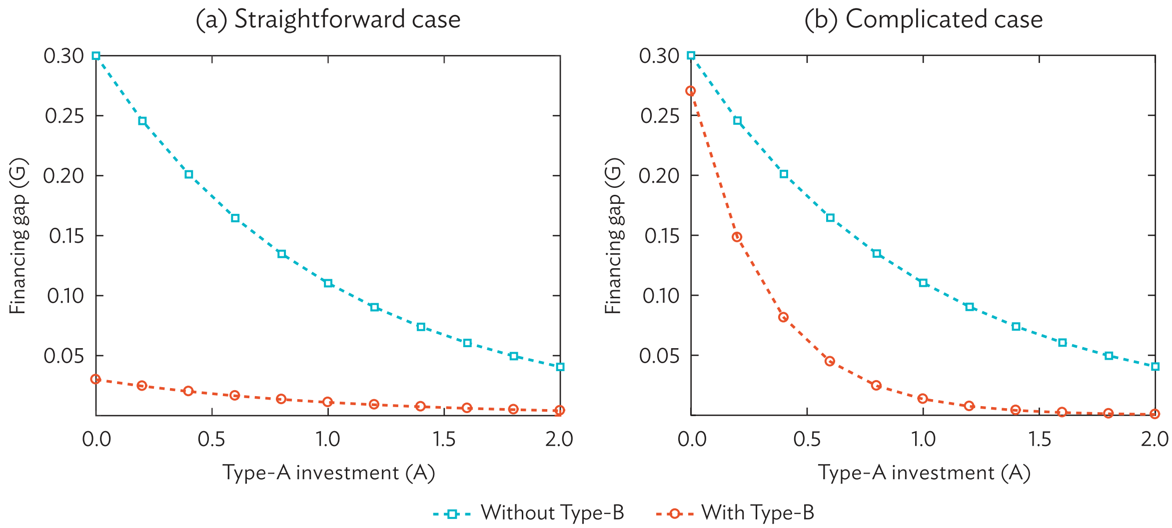
As noted, that information can be public or private and can be either manipulated or authentic. Type-B technology enables the bank to collect authentic data without the chance of being manipulated through both the public and private information source. Then, this information can be further classified as "straightforward" or "complicated" as we defined. In the "straightforward" case, we let $\lambda = 0.6$, $k = 0.5$, $t = 1$, $k_B = 0.1$, and $t_B = 0$. In this special case, as the information from Type-B technology can be directly used, we have:

$$\mu_B(0) = 0; \frac{\partial \mu_B}{\partial A} = 0 \tag{30}$$

thus, representing a substitutable case of Type-A and Type-B technologies as defined in Corollary 1. Whereas in the "complicated" case, we let $\lambda = 0.6$, $k = 0.5$, $t = 1$, $k_B = 0.9$, and $t_B = 2$. In this special case, when A is small, the two are complementary, whereas when A is large, the two become substitutable according to Proposition 5.

We next plot the financing gap in Figure 2. As we defined in the two parameter sets, Figure 2a illustrates the straightforward case where the Type-A investment substitutes the Type-B investment such that the financing gap reduced by investing in Type-B technology decreases with A. On the other hand, Figure 2b illustrates a complicated case where the financing gap reduced by the Type-B investment increases and then decreases with A, thereby exhibiting a complementary and then substitutable relationship between the two types of fintech.

Figure 2: Impact of Fintech Investments on the Financing Gap



Source: Authors.

VI. INVESTING IN FINTECH

In the previous section, to focus on the impact of fintech in closing the financing gap, we treated fintech as an exogenous investment. In this section, we consider the optimal level of fintech investment. We consider the investment decisions from two perspectives: a bank's and a social planner's.

A. A Bank's Fintech Investment

We first consider a bank's Type-A investment without Type-B technology. There, the bank's optimal Type-A fintech investment is determined through the following equation:

$$A^* = \arg\max_A \; N(R - R_0)c\lambda(1 - \mu) - A \tag{31}$$

Thus, A^* satisfies:

$$\frac{\partial \mu}{\partial A^*} = -\frac{1}{N(R - R_0)c\lambda} \tag{32}$$

As μ is convex in A, the above condition also uniquely determines A^*. Using the Envelope Theorem, we can obtain the following results.

Proposition 6. *Without Type-B technology, the bank's optimal Type-A investment (A^*) increases in the bank's size (N), the bank's profit margin ($R - R_0$), and the fraction of good firms (λ).*

Next, we consider the bank's Type-A investment with Type-B technology:

$$A_B^* = \arg\max_{\mathrm{A}}\ N(R - R_0)c\lambda(1 - \mu\mu_B) - A \tag{33}$$

Thus, A_B^* is determined by:

$$\mu\frac{\partial\mu}{\partial A_B^*} + \mu_B\frac{\partial\mu}{\partial A_B^*} = -\frac{1}{N(R - R_0)c\lambda} \tag{34}$$

Proposition 7. *With Type-B technology, the bank's optimal Type-A investment (A_B^*) increases in the bank's size (N), the bank's profit margin ($R - R_0$), and the fraction of good firms (λ). The bank's optimal Type-A investment with Type-B technology (A_B^*) is less than or equal to that without Type-B technology (A^*) if*

1. $\mu + \mu_B \leq 1$ *and* $\frac{\partial\mu}{\partial A} < \frac{\partial\mu_B}{\partial A}$ *for all A, or*
2. $\frac{\partial\mu_B}{\partial A} = 0.$

The second part of the proposition follows directly from Corollary 1.

Next, we consider the Type-B investment *B*. To do that, we compare the bank's profit under the optimal Type-A investment with and without Type-B technology:

$$\Pi^* = N(R - R_0)c\lambda(1 - \mu) - A^* \tag{35}$$

$$\Pi_B^* = N(R - R_0)c\lambda(1 - \mu\mu_B) - A_B^* \tag{36}$$

Using the Envelope Theorem, we have:

$$\frac{\partial\Pi^*}{\partial\lambda} = N(R - R_0)c(1 - \mu); \frac{\partial\Pi_B^*}{\partial\lambda} = N(R - R_0)c(1 - \mu\mu_B) \tag{37}$$

Therefore, as $\bar{B} = \Pi_B^* - \Pi^*$, we have that:

$$\frac{\partial\bar{B}}{\partial\lambda} = -N(R - R_0)c[\mu(A^*) - \mu(A_B^*)\mu_B(A_B^*)] \tag{38}$$

That is, the impact of λ on the Type-B investment threshold $\bar{B}$ depends on whether the Type-B technology can reduce the financing gap. The relationship between $\bar{B}$ and $(R - R_0)$ and N is similar. This leads to the following proposition.

Proposition 8. *There exists a threshold $\bar{B}$ such that the bank should invest in Type-B technology if and only if $B < \bar{B}$. In equilibrium, if Type-B technology can lower the financing gap, $\bar{B}$ decreases in λ, N, and $(R - R_0)$.*

We next apply the exponential form in equation (9) to obtain further insights:

Proposition 9.[8] *When $\mu = ke^{-tA}$ and $\mu_B = k_B e^{-t_B A}$, under the bank's profit maximization scenario, the optimal Type-A investments with and without Type-B technology are:*

$$A^* = \frac{\ln[ktN(R - R_0)c\lambda]}{t}; A_B^* = \frac{\ln[kk_B(t_B + t)N(R - R_0)c\lambda]}{t + t_B}$$

The corresponding financing gaps are:

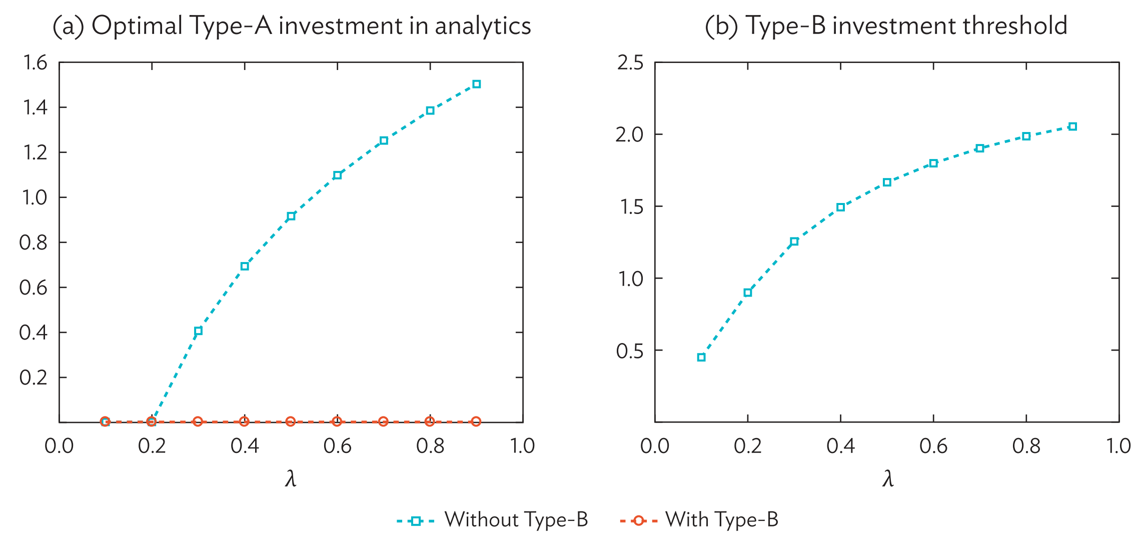
$$G^* = \frac{1}{t(N - R_0)c}; G_B^* = \frac{1}{(t + t_B)N(R - R_0)c} \tag{39}$$

Finally, the investment threshold for Type-B technology is:

$$\bar{B} = \frac{1 + \ln[kN(R - R_0)c\lambda] + \ln(t)}{t} - \frac{1 + \ln[kk_B N(R - R_0)c\lambda] + \ln(t + t_B)}{t + t_B} \tag{40}$$

Although the size and profit margin of the bank also matter, we are especially interested in how the fraction of good firms, λ, affect the bank's investment decision, as this represents market characteristics, and thereby can be used as an instrument by government and/or nonprofit organizations to motivate banks' fintech adoption. We again focus on the two extreme cases, the straightforward and the complicated, for illustration, see Figure 3 and Figure 4, respectively.

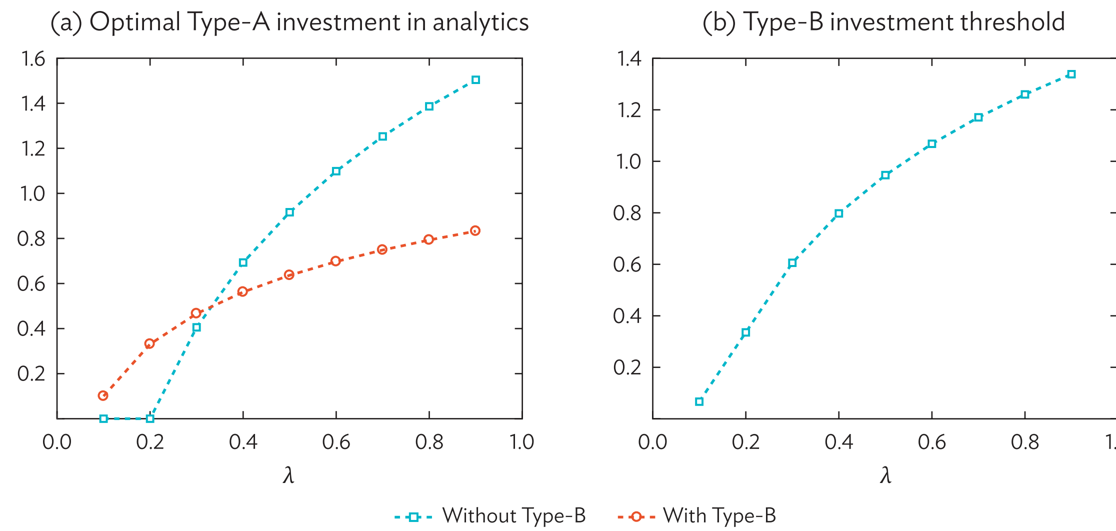
Figure 3: Optimal Fintech Investment When Information Is Straightforward



Source: Authors.

8 Proofs of propositions 9, 12, and 13 are shown in Appendix 2.

Figure 4: Optimal Fintech Investment When Information Is Complicated



Source: Authors.

Three observations are notable. First, when the information from Type-B technology is straightforward (Figure 3a), increasing the Type-A investment does not enhance the signal accuracy from Type-B technology, thereby resulting in a flat and zero line for the optimal Type-A investment with Type-B investment. In addition, the two types of fintech exhibit a substitutable relationship; investing in Type-B technology reduces the need to invest in Type-A technology. Without the Type-B investment, the optimal Type-B investment increases with the fraction of good firms λ as predicted by Proposition 6. When the fraction of good firms increases, it is more profitable in expectation for the bank to lend, and thus, it is more important to identify who to lend to so to avoid misclassification risks by investing in Type-A technology. However, the marginal benefit decreases with λ as it is easier and easier to lend when there are more good firms.

Second, when the information from Type-B technology is complicated, we observe the same concavely increasing pattern for both cases with and without Type-B technology (see Figure 4a). However, the complementary and then substitutable relationship between the two types of fintech depends on λ. Here, when λ is small, the optimal level of Type-A investment with Type-B investment is higher than that without. However, for large λ, the opposite relationship emerges.

Finally, we note that in both cases (Figures 3b and 4b), the investment threshold in Type-B fintech increases concavely with λ. This suggests that banks in markets where a larger fraction of firms are high-quality ones are more likely to invest in Type-B fintech.

B. Socially Optimal Fintech Investment

When maximizing social welfare (the sum of the bank and firm's payoff), the optimal Type-A investment A^S without Type-B technology is:

$$A^S = \arg\max_A N(R - R_0 + M)c\lambda(1-\mu) - A \tag{41}$$

in which $M = w/c - 1$ is the firm's profit margin.

Similarly, with Type-B technology, the optimal Type-A investment A_B^S is:

$$A_B^S = \arg\max_{\mathrm{A}} N(R - R_0 + M)c\lambda(1 - \mu\mu_B) - A \tag{42}$$

By solving these two problems, we have:

$$\frac{\partial \mu}{\partial A^S} = -\frac{1}{N(R - R_0 + M)c\lambda} \tag{43}$$

$$\mu \frac{\partial \mu_B}{\partial A_B^S} + \mu_B \frac{\partial \mu}{\partial A_B^S} = -\frac{1}{N(R - R_0 + M)c\lambda} \tag{44}$$

Proposition 10. *The socially optimal Type-A investment A^S (resp. A_B^S) is greater than A^* (resp. A_B^*). The underinvestment is more severe when the supplier's profit margin (M) is high.*

The intuition behind the underinvestment is clear: as the bank only enjoys a fraction of the benefit, it has no incentive to investment at the socially optimal level. Such underinvestment offers room for government and/or international organizations whose objective is more aligned with social welfare maximization to intervene.

Next, we consider the first-best Type-B investment decision. To do that, we compare the social welfare with and without Type-B technology.

$$\Pi^S = N(R - R_0 + M)c\lambda(1 - \mu) - A^S \tag{45}$$

$$\Pi_B^S = N(R - R_0 + M)c\lambda(1 - \mu\mu_B) - A_B^S \tag{46}$$

Proposition 11. *There exists a threshold $\bar{B}^S$ such that it is optimal to invest in Type-B technology if and only if $B \leq \bar{B}^S$. In equilibrium, if Type-B technology can lower the financing gap, $\bar{B}^S$ decreases in λ, N, $(R - R_0)$, and M.*

Regardless of whether a bank is a profit-maximizer or social-optimizer, the threshold $\bar{B}^S$ exhibits a similar pattern as the threshold $\bar{B}$. For additional insights, we resort to the exponential form in the following proposition.

Proposition 12. *When $\mu = ke^{-tA}$ and $\mu_B = k_B e^{-t_B A}$, under the social welfare maximization scenario, the optimal Type-A investments with and without Type-B technology are:*

$$A^S = \frac{\ln[ktN(R - R_0 + M)c\lambda]}{t}; A_B^S = \frac{\ln[kk_B(t_B + t)N(R - R_0 + M)c\lambda]}{t + t_B}$$

The corresponding financing gaps are:

$$G^S = \frac{1}{tN(R - R_0 + M)c}; G_B^S = \frac{1}{(t_B + t)N(R - R_0 + M)c} \tag{47}$$

Finally, the investment threshold for Type-B technology is:

$$\bar{B}^S = \frac{1 + \ln[kN(R - R_0 + M)c\lambda] + \ln(t)}{t} - \frac{1 + \ln[kk_B N(R - R_0 + M)c\lambda] + \ln(t + t_B)}{t + t_B} \tag{48}$$

Several observations are notable. First, regarding the impact of Type-B technology in closing the financing gap, it is clear that $G_B^* \leq G^*$ (and $G_B^S \leq G^S$). With simple algebra, we can also see that $G^S - G_B^S \leq G_B^* - G^*$, indicating that, under the optimal investment level, Type-B technology can help further close the financing gap than under the socially optimal level. As a result, although profit-maximizing banks tend to underinvest than socially optimizing banks, governments could encourage and lower the entry barrier for Type-B technology adoption as Type-B technology, in this case, can help further close the financing gap.

Second, by comparing $\bar{B}$ and $\bar{B}^S$, we have:

$$\bar{B}^S - \bar{B} = \left(\frac{1}{t} - \frac{1}{t + t_B}\right) \ln\left(1 + \frac{M}{R - R_0}\right) > 0 \tag{49}$$

We note that the underinvestment in Type-B technology is more severe when the signal quality related to the information collected under Type-B technology is more sensitive to the Type-A investment, and when the firm's profit margin is higher relative to the bank's.

Finally, we consider a special case (i.e., the straightforward case), where $t_B = 0$, that is, Type-A technology cannot improve the signal quality based on information collected by Type-B technology. In this case, the above proposition leads to:

$$G^S = G_B^S \tag{50}$$

This result reveals that under this specific functional form, Type-B technology cannot help close the financing gap when Type-A technology cannot improve the signal quality based on information collected by Type-B technology. Relatedly, we have:

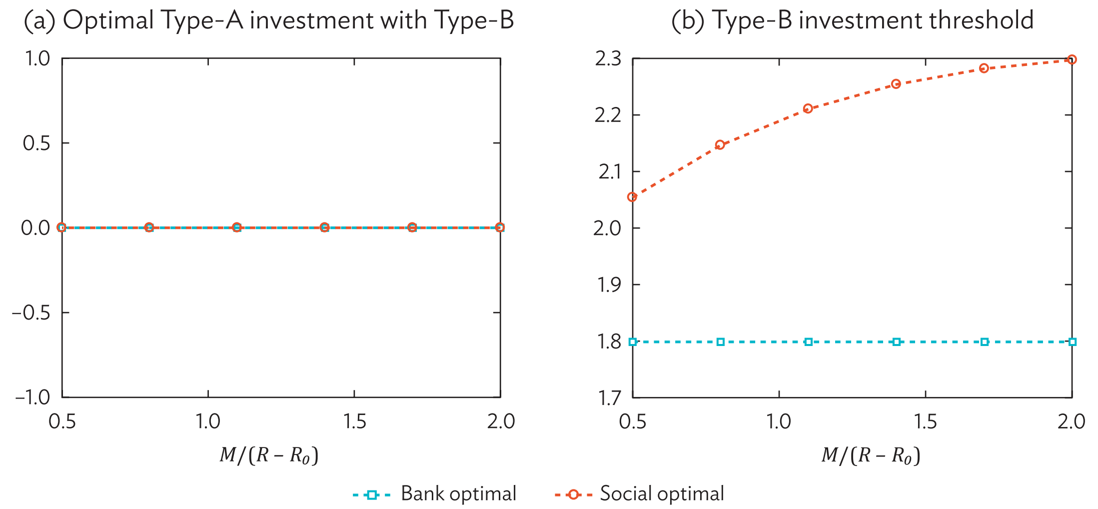
$$\bar{B} = \bar{B}^S = -\frac{\ln(k_B)}{t} \tag{51}$$

That is, the Type-B investment threshold is only influenced by the efficiency of the Type-A investment, as measured by t, and the accuracy of the signal based on the information collected by Type-B technology (k_B).

Finally, we plot the straightforward and complicated cases in Figures 5 and 6, respectively. When the new information from Type-B technology is straightforward, regardless of the magnitude of $\frac{M}{R-R_0}$, with Type-B technology, the bank's optimal and the socially optimal Type-A investment are both zero (see Figure 5a), and in this case, it is easier for the bank to adopt Type-B technology. Governments should improve data infrastructure, making data more accessible, and allow alternative data for regulatory purposes.

When the new information from Type-B technology is complicated, we observe that the socially optimal Type-A investment is greater than the bank's optimal Type-A investment, confirming the underinvestment issue in Proposition 10, and such an underinvestment issue is more severe with high M. In this case, governments should improve public data quality and enable data aggregation (e.g., credit scoring).

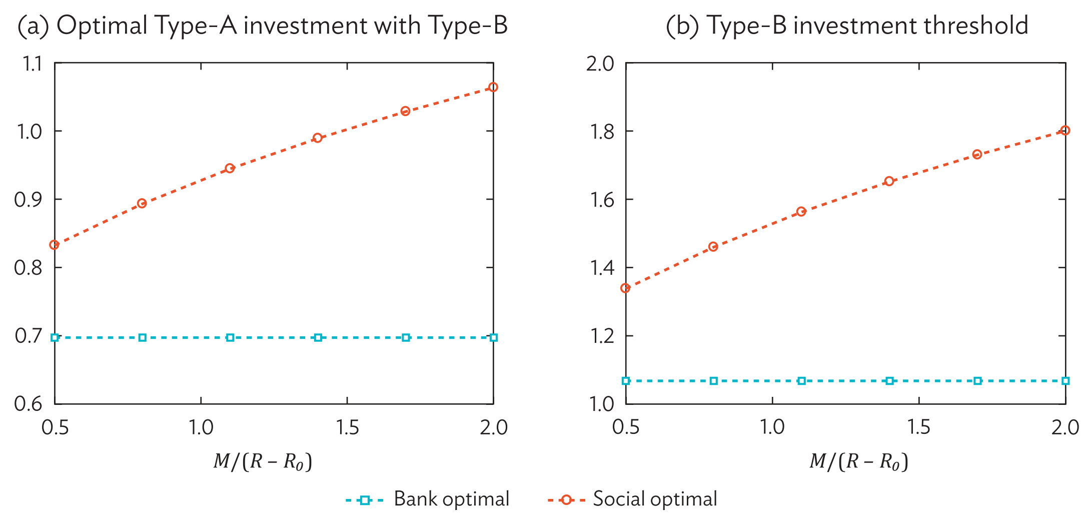
Figure 5: Difference between Bank Profit Maximizing Investment Level and Socially Optimal Level When the Information Is Straightforward



Notes: M refers to the firm's profit margin. $R - R_0$ is the bank's profit margin.

Source: Authors.

Figure 6: Difference between Bank Profit Maximizing Investment Level and Socially Optimal Level When the Information Is Complicated



Notes: M refers to the firm's profit margin. $R - R_0$ is the bank's profit margin.

Source: Authors.

Finally, we note that banks' underinvestment in fintech is double marginalization. To resolve such underinvestment, one intuitive solution is for the bank to charge borrowers a fee for fintech adoption. Such a solution, however, faces its own challenges. First, under the existing competition landscape, after fintech investment is sunk, the bank may not have the pricing power to charge borrowers extra fees. In addition, passing the fees to exporters, which inevitably lowers the exporters' profit, may have other unintended consequences, such as trade volume reduction, and adverse selection.

As a result, addressing the issue of underinvestment in fintech calls for innovative market mechanisms as well as collaborations between public and private sector players. It highlights opportunities for governments and policy makers to impose incentives to restore the misaligned interests between financial institutions and financially stressed firms. Possible means include, but not limited to, tax benefits for financial institutions to adopt fintech tools, technology assistance programs for these financial institutions to learn and adopt new technologies, government platform for blockchain or AI, and provide protocols and standards for firm identity.

VII. CONCLUSIONS

Financially constrained MSMEs rely on external finance to sustain and grow their businesses, and yet, these firms are also the ones that receive the most trade finance rejections. Information asymmetry between these firms and financial institutions is one main reason for the rejections. In this paper, we consider two players—a bank and exporters that need external finance—and investigate how fintech tools can help alleviate the finance gap due to information friction. We first identify the financing gap by maximizing the banks' profit without fintech (benchmark case), then identify the gap by maximizing bank's profit with investment in Type-A technology and/or in Type-B technology (case with fintech), and finally identify the gap by maximizing social welfare (socially optimal case).

By comparing the benchmark case with the case with fintech, we find that both types of technologies help in closing the financing gap by providing a more accurate signal to identify the creditworthy exporters to finance, and the power of fintech can be more profound if there exists a greater portion of creditworthy ones. Nonetheless, the two types of technologies may complement or substitute each other. The investment in Type-B technology is more likely to complement (substitute) the investment in Type-A technology when this Type-A investment is low (high), and when the Type-A investment does not help improve the information collected by Type-B technology, then the two become substitutes. Regardless of the investment in fintech, the bank's optimal Type-A investment increases in bank size, its profit margin, and the fraction of good exporters in its application pools. As to the decision whether to invest in Type-B technology, this depends on whether Type-B technology can lower the financing gap, and if yes, the bank is more likely to invest in Type-B technology when the bank size, its profit margin, and the associated fraction of good exporters are high.

On the other hand, by comparing the socially optimal case with the case with fintech, we find that the bank will underinvest in Type-A technology and/or Type-B technology. Understandably, the bank only extracts a portion of the benefits from the fintech investment, whereas the exporter firm extracts the rest. Such double marginalization leads to banks' underinvestment in fintech. Such underinvestment is more severe when the exporters' margin is high. This calls for tax incentives to encourage fintech adoption by financial institutions as well as for private and public sector collaboration to improve credit data quality and promote digital standards.

As an initial attempt to model the role of fintech in reducing information friction in a supply chain finance setting, this paper can be extended in three directions. The first is at the exporter firm level. In our current model, the wholesale price and order quantity are exogenous. Future study could consider endogenizing these two operational decisions for each firm. The second direction is at the bank level. In our current setup, we consider the case in which exporters will file their loan applications to the bank. In practice, exporters can also choose the bank(s) that they want to do business with. In the presence of various transaction costs (e.g., long know-your-customer time, high interest rates, etc.), banks could use fintech as a screening mechanism. Anticipating faster and more accurate lending decisions from those fintech banks, high-quality exporters are more likely to be drawn to those banks, thereby increasing fintech banks' profit. Finally, from the policy maker's perspective, we can examine the effectiveness of various incentive schemes to promote fintech adoptions and investment, thereby improving social welfare.

APPENDIX 1: FINTECH INVESTMENT WHEN SIGNAL QUALITY FOLLOWS A POLYNOMIAL FUNCTION FORM

In the main body of the paper, in addition to deriving analytical results based on general technical assumptions, we present numerical results under the assumption that the impact of fintech investment on the quality of the signal follows an exponential function form in equation (9). In this appendix, we replace the exponential form by the following polynomial functional form:

$$\mu = k(1 + A)^{-t}; \mu_B = k_B \tag{A.1}$$

The following proposition reveals that the main insights remain unchanged.

Proposition 13. *When* $\mu = k(1 + A)^{-t}$ *and* $\mu_B = k_B$,

Under the bank's profit maximization scenario, the optimal Type-A investments with and without Type-B technology are:

$$A^* = [ktN(R - R_0)c\lambda]^{\frac{1}{1+t}} - 1; A_B^* = [kk_BtN(R - R_0)c\lambda]^{\frac{1}{1+t}} - 1$$

The corresponding financing gaps are:

$$G^* = (k\lambda)^{\frac{1}{1+t}}[Nt(R - R_0)c]^{-\frac{t}{1+t}}; G_B^* = (kk_B\lambda)^{\frac{1}{1+t}}[Nt(R - R_0)c]^{-\frac{t}{1+t}} \tag{A.2}$$

Finally, the investment threshold for Type-B technology is:

$$\bar{B} = \left[1 - (k_B)^{\frac{1}{1+t}}\right]\left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kN(R - R_0)c\lambda]^{\frac{1}{1+t}} \tag{A.3}$$

Under the social welfare maximization scenario, the optimal Type-A investments with and without Type-B technology are:

$$A^S = [ktN(R - R_0 + M)c\lambda]^{\frac{1}{1+t}} - 1; A_B^S = [kk_BtN(R - R_0 + M)c\lambda]^{\frac{1}{1+t}} - 1$$

The corresponding financing gaps are:

$$G^S = (k\lambda)^{\frac{1}{1+t}}[Nt(R - R_0 + M)c]^{-\frac{1}{1+t}}; G_B^S = (kk_B\lambda)^{\frac{1}{1+t}}[Nt(R - R_0 + M)c]^{-\frac{t}{1+t}} \tag{A.4}$$

Finally, the investment threshold for Type-B technology is:

$$\bar{B}^S = \left[1 - (k_B)^{\frac{1}{1+t}}\right]\left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kN(R - R_0 + M)c\lambda]^{\frac{1}{1+t}} \tag{A.5}$$

Two observations are notable. First, under this specification, even when Type-A technology does not influence the signal related to Type-B technology, that is, $\partial\mu_B/\partial A = 0$, we still find that Type-B technology helps further close the financing gap, that is, $G^* > G_B^*$ and $G^S > G_B^S$. This observation indeed indicates the importance to estimate a right form. Nonetheless, we note that

$$\bar{B}^S - \bar{B} = \left[(k_B)^{\frac{1}{1+t}} - 1\right]\left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kN(R - R_0)c\lambda]^{\frac{1}{1+t}}\left[1 - \left(1 + \frac{M}{R - R_0}\right)^{\frac{1}{1+t}}\right] > 0 \qquad \text{(A.6)}$$

Consistent with the previous specification, the investment threshold for Type-B technology is higher under the socially optimal level than under the bank profit maximization level.

APPENDIX 2: PROOFS

Proof of Propositions 9 and 12. *Under the bank profit maximization scenario, substituting* $\mu = ke^{-tA}$ *and* $\mu_B = k_B e^{-t_B A}$ *into* Π^*, Π_B^**, we have:*

$$A^* = \frac{\ln[ktN(R-R_0)c\lambda]}{t}; A_B^* = \frac{\ln[kk_B(t_B+t)N(R-R_0)c\lambda]}{t+t_B}$$

Thus, the resulting μ and μ_B are:

$$\mu(A^*) = \frac{1}{tN(R-R_0)c\lambda}; \mu(A_B^*)\mu_B(A_B^*) = \frac{kk_B}{(kt_B+k_Bt)N(R-R_0)c\lambda} \tag{B.1}$$

which leads to the financing gaps as in the proposition.

Under such investment levels, the bank's profits are:

$$\Pi^* = N(R-R_0)c\lambda - \frac{1+\ln[ktN(R-R_0)c\lambda]}{t} \tag{B.2}$$

$$\Pi_B^* = N(R-R_0)c\lambda - \frac{1+\ln[kk_B(t_B+t)N(R-R_0)c\lambda]}{t+t_B} \tag{B.3}$$

Therefore, $\bar{B}$ follows:

$$\bar{B} = \frac{1+\ln[kN(R-R_0)c\lambda]+\ln t}{t} - \frac{1+\ln[kk_BN(R-R_0)c\lambda]+\ln(t+t_B)}{t+t_B} \tag{B.4}$$

For a special case, when $t_B = 0$, we have:

$$\bar{B} = -\frac{\ln(k_B)}{t} \tag{B.5}$$

Similarly, under the socially optimal investment level, we have:

$$A^S = \frac{\ln[ktN(R-R_0+M)c\lambda]}{t}; A_B^S = \frac{\ln[kk_B(t_B+t)N(R-R_0+M)c\lambda]}{t+t_B} \tag{B.6}$$

and the financing gaps are:

$$G^S = \frac{1}{tN(R-R_0+M)c}; G_B^S = \frac{1}{(t_B+t)N(R-R_0+M)c} \tag{B.7}$$

and the social welfares are: It is clear that $G_B^S \leq G^S$ and the equality holds only if $t_B = 0$.

Proof of Proposition 13. *Under the bank profit maximization scenario, without Type-B technology, by substituting* $\mu = k(1+A)^{-t}$ *and* $\mu_B = k_B$ *into* Π^**, we have:*

$$kt(1+A^*)^{-t-1} = \frac{1}{N(R-R_0)c\lambda} \tag{B.8}$$

Therefore, we can derive,

$$A^* = [ktN(R-R_0)c\lambda]^{\frac{1}{1+t}} - 1 \tag{B.9}$$

and the resulting signal quality μ is:

$$\mu(A^*) = k[ktN(R-R_0)c\lambda]^{-\frac{t}{1+t}} \tag{B.10}$$

The corresponding financing gap is:

$$G^* = (k\lambda)^{\frac{1}{1+t}}[Nt(R-R_0)c]^{-\frac{t}{1+t}} \tag{B.11}$$

The bank's profit is:

$$\Pi^* = N(R-R_0)c\lambda - \left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kN(R-R_0)c\lambda]^{\frac{1}{1+t}} + 1 \tag{B.12}$$

Similarly, by considering the case with Type-B technology, we have:

$$A_B^* = [kk_BtN(R-R_0)c\lambda]^{\frac{1}{1+t}} - 1, \tag{B.13}$$

$$\mu(A^*) = k[kk_BtN(R-R_0)c\lambda]^{-\frac{t}{1+t}}, \tag{B.14}$$

$$G_B^* = (kk_B\lambda)^{\frac{1}{1+t}}[Nt(R-R_0)c]^{-\frac{t}{1+t}}, \text{ and} \tag{B.15}$$

$$\Pi_B^* = N(R-R_0)c\lambda - \left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kk_BN(R-R_0)c\lambda]^{\frac{1}{1+t}} + 1 \tag{B.16}$$

By comparing Π^* and Π_B^*, we have:

$$\bar{B} = \left[1-(k_B)^{\frac{1}{1+t}}\right]\left(t^{\frac{1}{1+t}} + t^{-\frac{t}{1+t}}\right)[kN(R-R_0)c\lambda]^{\frac{1}{1+t}} \tag{B.17}$$

The results under the socially optimal investment level are similar and the details are omitted.

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The Role of Fintech in Mitigating Information Friction in Supply Chain Finance

Recent advances in financial technology (fintech), such as blockchain and artificial intelligence, could help improve the efficiency of supply chain finance. This paper's conceptual and analytical framework studies how fintech reduces "information friction" to help close the financing gap by lowering the probability of a good firm being misclassified as bad. "Double marginalization" makes a bank's optimal fintech investment level lower than the socially optimal level. This calls for mechanisms to incentivize or complement banks' investment in fintech.

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