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

Hsiao-Hui Lee
National Chengchi University, hsiaohui@nccu.edu.tw

S. Alex Yang
London Business School and University of Hong Kong, sayang@london.edu

Kijin Kim
Economic Research and Regional Cooperation Department, Asian Development Bank, kijinkim@adb.org

Micro, small and medium enterprises (MSMEs) in developing countries face severe financing difficulties, especially when trying to grow their businesses internationally. One significant cause of this financing gap is informational friction. Various supply chain finance products and solutions are introduced to mitigate such frictions by leveraging on information from the extended supply chain of the borrower. The recent development in FinTech, which is closely related to information technologies, has offered new opportunities to further improve the efficiency of supply chain finance. In this paper, we propose a conceptual and analytical framework to study how FinTech can close the financing gap by reducing information friction. Under this framework, we classify various types of FinTech into two categories: information processing technology and information collecting technology. The former one (denoted as Type-A), including analytics and artificial intelligence, allows financial institutions to efficiently process and transform raw data into useful information (signals) that can directly guide the decision-making process. The latter one (denoted as Type-B), including blockchain, biometrics and identity management, and digitalization, allows financial institutions to collect additional and accurate data/information to be processed in the decision-making process. Using this framework, we find that both types of FinTech help closing the financing gap by lowering the probability that a good firm is mis-classified as a bad one. The two types of FinTech can be complements or substitutes. 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, the bank’s optimal FinTech investment level is lower than the socially optimal level. This calls for additional mechanisms that simulate or complement banks’ investment in FinTech.

Key words: FinTech, Supply Chain Finance, Trade Finance, information, Analytics, AI, Blockchain, Digitalization

History: First draft: April 4, 2019; current draft: June 6, 2019

1. Introduction

Micro, small and medium enterprises (MSMEs) in developing countries rely on external finance to sustain their operations and grow their business, both domestically and internationally. Among
various financing sources, trade finance is an important form. In practice, three trade finance modes are commonly used: cash-in-advance, letter of credit, and open account (e.g., see Antras and Foley 2015, Foley et al. 2010, and Schmidt-Eisenlohr 2013). Cash-in-advance terms require importers to pay exporters before they ship the goods, thus imposing the needs to secure finance to importers. On the other hand, letter of credit terms requires banks to commit payments before exporters produce the goods and to pay the exporters upon shipping, thus eliminating exporters’ risks of not receiving payments. Finally, open account (trade credit) terms allows importers to pay exporters at certain time after the receipt of the goods, thus imposing high importer repayment risks to exporters. Because of the flexibility for importers to resell the goods before paying exporters, open account terms are prevalent under current competitive business environment (Foley et al. 2010).

In addition, as the importers do not have to pay the exporters until the goods are received and inspected under open accounts, it protects the importers from the exporter’s performance risk, i.e., the risk that exporters’ may not be able to deliver the order as contractually specified. As such, it is popular in trades between exporters in the developed world and importers from the emerging markets, where the payment risk is in general low while the performance risk could be high. Despite their advantages and popularity, compared to cash-in-advance and letter of credits, open accounts inevitable aggravates the already challenging financial situations faced by MSMEs in developing countries. Various open accounts based trade finance products and programs, also commonly known as supply chain finance,1 have been introduced by financial institutions and national, regional, and international organizations. Among them, purchase order and receivable finance have increasingly received attentions, especially for financially constrained exporters without collaterals.

Despite these trade finance products and programs, MSMEs continue to face challenges in accessing finance. According to the 2017 Trade Finance Gaps, Growth, and Jobs Survey by Asian Development Bank (Di Caprio et al. 2017), approximately 40% of worldwide proposal (i.e., firm requests to banks for trade finance) rejections are from Asia and Pacific, and among this 40% rejections, MSMEs and mid-cap firms accounts for 74% of rejections. Such a finance gap adversely impact the growth of such firms, and hinted their role in job creation. According to the same survey, once a loan application is rejected, about 60% of responding firms from the ADB survey reported that they failed to execute their contracts. This leads to significant losses in trade. Moreover, the ADB survey points out that 36% of trade finance rejections could have been funded. Many reasons that banks reject trade finance applications leads to the existence of information friction. For example,

---

1 In this paper, we refer to supply chain finance as any form of financial products and solutions that leverage on information from the extended supply chain, and, hence, it covers both domestic and international transactions. As it is easier for banks to retrieve their funds in domestic transactions, we focus on international transactions in our discussion.
about 29% out of the 36% rejections is due to the failure to meet the regulation on Know Your Customer (KYC). Banks nowadays face great challenges in compliance. For example, HSBC agreed to pay a $1.9 billion U.S. fine for allowing itself to be money launderer in 2012 (Viswanatha and Wolf 2012). As such, banks need to exert a great effort in their KYC process in order not to violate laws and regulations. However, given the small sizes of MSMEs, such a complicated and time consuming process thus prohibits banks in initiating relationships with these clients, resulting in significant information friction issues during the loan approval process. And 21% of rejections are related to insufficient collateral or information.

In responding to the difficulty of resolving information frictions, financial institutes may benefit from the advancement of technology by responding to finance needs faster and more efficiently. An ongoing initiative for banks is digitalization. According to the ADB survey, about 80% of responding banks expect a cost reduction in their loan approval process, including facilitating KYC checks, reducing costs of due diligence, and enhancing ability to access risks of small clients.

Interestingly, in the same survey, such an initiative on digitalization alone does not seem to reduce rejection rates for small firms, and such an observation reflects the challenge banks face in reducing information friction. Although digitalization does facilitate the loan process efficiency and is the first step for other advanced technology adoption, it alone does not help collect more useful data nor enable better information processing capability for banks. In addition to digitalization, banks are searching for FinTech tools that enable them to extract more and better use information so to reduce information frictions. A PwC report on global FinTech investment (see an extraction from the report in Figure 1) reveals a strong focus on information. Therefore, in this paper, we focus on financial technologies that help alleviate information frictions. Depending on the specific role such technologies play, we and classify these technologies into two categories: information processing technology and information collecting technology.

Information processing technologies refer to technologies that convert a vast amount of raw data that banks own (or could obtain) into useful information in lending decisions. Leveraging on the effort of digitalization, banks now have an enormous amount of data that are ready to be analyzed. Two prominent examples that financial institutions have started to adopt are advanced analytics and Artificial Intelligence (AI). According to 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 anti-money-laundering structure to prevent frauds.

Information collection technologies refer to those that collect additional new data, such as digitization and automation, biometrics and identity management, and blockchain. For example, using a new technology, COiN, JPMorgan Chase reduces a significant amount of time in reviewing documents and extracting data; reviewing 12,000 documents originally require more than 360,000
hours of work, but using COiN only needs seconds. 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 the stakeholders along supply chains) can accurately link information from various channels, such as ports, airports, and custom (e.g., A vessel sailing to Singapore port containing shipments to Carrefour, a big supermarket chain in Singapore). Finally, large financial institutes also start to invest in blockchain to enhance their digitalization efforts as well as to collect additional information with superior accuracy and transparency. Jointly with Reliance Industries and Tricon Energy, HSBC and ING banks adopted blockchain in their trade finance transactions (HSBC 2018). Quoted from Ajay Sharma, the Regional Head of Global Trade and Receivables Finance of Asia Pacific for HSBC, 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.” The Joint Chief Financial Officer of Reliance Industries, Srikanth Venkatachari, said, “use of blockchain in trade finance enhances transparency, security and synergy across all the parties and stakeholders involved.” 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, the recent effort of promoting digital standards, legal entity identifiers, and legislation related digitalizing trade documents are also related to information collection technologies as they enable more efficient collection of information through multiple sources.

Although these technologies are all aiming 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 status of transactions. In addition to blockchain, other applications have also leveraged traditional platforms to collect more data. For example, GT Nexus (rebranded to be Infor Nexus in 2019) collects supply chain information from suppliers, manufacturers, brokers, third-party logistics providers, banks, among others. Such a service enables firms in 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 decision without the need to be further processed.

On the other hand, 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 via 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 such 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 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, etc.\(^2\) 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 in order 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.

The advancement of technology especially benefits MSMEs by responding to their financing needs more efficiently at lower costs. Yet, the role of different type of FinTech tools in facilitating trade is still under-explored in such a context. With a focus on how financial technology can play a role in enhancing access to trade finance for MSMEs, we study how trade finance products can contribute to reduce the unmet demand for trade finance by taking advantage of technology. In this paper, we focus on supply chain finance products based on open account (trade credit), in particular receivables finance and purchase order finance. Manova (2012) shows how financial market imperfection distorts international trade, and such a financial friction is more profound for financially constrained exporters than domestic producers for higher working capital needs due to longer shipping time. To reduce finance gaps, an intuitive approach is to facilitate trade finance for the 36% of rejected trade finance transactions as mentioned in the ADB 2017 survey. These are

\(^2\) A customer needs to provide the login information to Kabbage to receive a loan approval for up to 250,000 US dollar. See [https://www.kabbage.com/how-it-works/qualifying/](https://www.kabbage.com/how-it-works/Qualifying/).
transactions that banks, with more information, could have funded. Thus, we focus on exporters’ need of finance before importers pay their bills. Moreover, financially unconstrained firms may raising finance using their collateral, and hence may be less likely to be in these 36% rejected transactions. As a result, we tackle the situation for exporters only equipped with purchase orders or receivables in this paper.

In sum, this paper studies how FinTech can close the trade financing gap by reducing information friction, in which we classify various types of FinTech into two categories: information processing technology and information collecting technology. The former one (Type-A), including data analytics and AI, allows financial institutions to better process raw data and transform them into useful information that can directly guide the decision-making process. The latter one (Type-B), on the other hand, include blockchain, biometrics and identity management, and digitalization, and it allow more data/information to be collected in decision-making. We find that both types of FinTech tools help closing financing gaps by offering a more accurate signal to identify the good firms that deserve loans. Next, we study the bank’s investment decisions, and find that the bank’s Type-A investment increases in the bank’s size, profit margin, and the fraction of good firms in the market. The two types of FinTech can be complements or substitutes 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 the 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. This calls for additional mechanisms supported by public sectors, including governments and international organizations such as the International Standards Organization (ISO), the World Customs Organization, and International Chamber of Commerce (ICC), that simulate or complement banks’ investment in FinTech. In particular, public sectors can support mechanisms to lower the cost of technology adoption such that it is easier and cheaper for banks to adopt FinTech tools. These mechanisms include, but 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,

3 For blockchain and biometrics, they also strengthen data security, which may not be functioning in the same way as digitalization 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 ISO 90001 and/or ISO 14001 certifications and accounting frauds).

4 Double marginalization is a common phenomenon in supply chains, where two parties at different vertical levels exercising 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 it importer customer above its marginal cost.
Lee, Yang, and Kim: The Role of FinTech in Mitigating Information Friction in Supply Chain Finance

and implementing rules and legislation for digital trade to lower banks’ legal risks for adopting new technologies.

The rest of the paper is organized as follows. We summarize the related literature in Section 2. In Section 3, we introduce a parsimonious model that captures the trade financing gap and the role of FinTech. Sections 4 and 5 assess how FinTech can help closing the trade financing gap. The bank’s investment in FinTech is discussed in Section 6. We conclude the paper in Section 7.

2. Literature Review

Our 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/exporters with banks and discussion in this literature stream is mostly surrounded around the choice between cash-in-advance, open account, and letter of credit terms. Antras and Foley (2015) study how the cash-in-advance, open account and letter of credit terms support international trade. Similar to their setup, we also consider importers’ repayment risks as well as exporters’ quality risks. In a similar setup, Schmidt-Eisenlohr (2013) consider a profit maximization problem for exporters and discuss 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 et al. (2016) use the data from World Bank Enterprise Survey to show that country characteristics significantly influence exporters’ payment contract choice. 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 the data provided by the Society for Worldwide Interbank Financial Telecommunications (SWIFT) and find that U.S. 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 U.S. exports to that country.

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 a significant amount of attentions in academia. The main focus in that stream of research 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). We refer the readers to Lee et al. (2018) and Chod et al. (2019) for recent summaries of the trade credit literature.

Despite its various advantages, trade credit inevitably increases the supplier’s financial burden. Consequently, various other supply chain finance products and solutions are invented. The most commonly used one is receivable finance, such as factoring (Klapper 2006), reverse factoring, or dynamic discounting (Hu et al. 2018). Such products relay on completed transactions between the buyer and seller. Another related product is trade credit insurance (Yang et al. 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 not often not sufficient to meet MSME’s financing need, especially for those who are looking to grow their business. More recently, academics have started to examine supply chain financing mechanisms that do not rely on completed transactions. Among them, Tang et al. (2018) compare purchase order finance (POF) with buyer direct finance (BDF), 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 et al. (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 our paper, we focus on the interaction between banks and exporters via purchase order and receivable finance and discuss how FinTech adoption can help resolve information asymmetry issues. Compared to the aforementioned papers in the supply chain finance literature, which often focus on the relationship between importers (buyers) and exporter (suppliers), instead of banks and the two parties, our paper focuses on how FinTech enables banks to make better lending and investment decisions.

Finally, the recent emergence of FinTech has attracted the attention of not only practitioners, but also academics. Stringent regulations and compliances, strong competition from new entrants, and rising costs push financial industries to embrace new financial technology. Philippon (2015) points out that the inefficiency in the U.S. 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 digitalization and automation in payment, trading, and customer services, blockchain, artificial intelligence and machine learning, cryptocurrencies, peer-to-peer lending and crowd-fundings. Although the regulations and policy makings may still need to be optimized (Philippon 2016), the FinTech movement does create opportunities and competitions for financial institutions. The adoption of blockchain by HSBC and ING and AI-enabled process improvement
by Citibank and JPMorgan Chase serve as great examples on how banks take advantages of the opportunities. Whereas, 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) shows 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 who 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 via information friction resolution, and consider how policy makers and governments can promote the adoption of these FinTech tools.

3. Model Setup

Consider a bank facing a group of $N$ homogenous MSME business borrowers without any initial endowment. Each supplier submit 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 (POF) setting and receivable financing (e.g., factoring and reverse factoring) setting. Under the POF setting, the supplier has secured a purchasing order from an oversea 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 POF. The interpretation under the receivables financing setting is similar. In the following, we will focus on the POF 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 incapable (bad, $L$ for low-type), each with their own distribution of future payoff, $\Pi$,

---

5 In principle, our model applies both MSME borrowers and large business borrowers. However, it is mainly focused on MSME as large firms would normally have other means to obtain financing, for example, by using collaterals or through public markets.
and the CDF and PDF of $\Pi_i$ 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 the other. 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:

$$E[\Pi_H] > Rc > E[\Pi_L].$$

(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,

$$\lambda E[\Pi_H] + (1 - \lambda) E[\Pi_L] < Rc.$$

(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, $\Pi_H$ equals to $w$ with probability 1, and $\Pi_L$ 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 re-written as:

$$w > Rc > [\lambda + (1 - \lambda)p]w.$$

(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 one is subject to 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 is that the firm is good. And the bank then use 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, IT equipments, etc.

2. Information Collecting Technology (Type-B): Type-B technology, such as Blockchain, biometrics, and digitalization, makes second source of 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/digitalization service from a platform, the initial investment in technology adoption often involves revamping the 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 firm 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 useful signal. The substitutability and/or complementarity of Type-A and Type-B technologies depend on how information conveyed in Type-B technology is processed in generating useful signal, which we will discuss in details later.

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

$$\Pr(\theta = 0 | \text{good}) = \mu.$$  \hspace{1cm} (4)

On the other hand, when the supplier’s bad, it cannot be mis-classified as good. That is:

$$\Pr(\theta = 1 | \text{bad}) = 0.$$  \hspace{1cm} (5)

Both the signal $\theta$ and the mis-classification risk $\mu$ are functions of the FinTech investment. Specifically, let $A$ to represent the Type-A investment level, and the function $\mu$ is parameterized by $A$. Intuitively, $\mu$ is convexly decreasing in $A$, that is:

$$\frac{\partial \mu}{\partial A} < 0; \quad \frac{\partial^2 \mu}{\partial A^2} > 0.$$  \hspace{1cm} (6)
For a micro-foundation of the model, let $A$ captures 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, i.e., 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 established track record.

The information gained from Type-B technology works similarly; the bank also access this second source of information, which is used to generate a signal. Let the signal of the Type-B information be $\theta_B$, and let the corresponding mis-specification risk be $\mu_B$, which is also influenced by the Type-A investment $A$.

$$\frac{\partial \mu_B}{\partial A} \leq 0; \quad \frac{\partial^2 \mu_B}{\partial A^2} \geq 0.$$  

(7)

Without loss of generality, similar to Biais and Gollier (1997), we assume $\theta$ and $\theta_B$ be independent, that is,

$$\Pr(\theta = 1 | \theta_B) = \Pr(\theta = 1);$$  

(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, under the general assumption of $\mu$ and $\mu_B$, we examine an exponential functional form:

$$\mu = ke^{-tA}; \quad \mu_B = k_Be^{-t_BA}.$$  

(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 are to the Type-A investment. Based on this specification, it is easy to see that small $k$ and $k_B$ and small $t$ and $t_B$ correspond to the case where the information is straightforward. That is, the raw data itself can lead to 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.

4. Closing the MSME 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 fail 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.
4.1. 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 (non-blockchain) signal being good \((\theta = 1)\), which is

\[
\Pr(good \mid \theta = 1) = 1.
\]  

(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 \(\theta\). Following the same notation as \(R\), we denote \(R_b(\theta = 1) = R\). Correspondingly, the bank’s profit is:

\[
\pi_b(\theta = 1) = N(R - R_0)\Pr(\theta = 1)c = N(R - R_0)c\lambda(1 - \mu).
\]  

(11)

Clearly, the bank’s profit is decreases in \(\mu\).

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

\[
\Pr(good \mid \theta = 0) = \frac{\lambda\mu}{\lambda\mu + (1 - \lambda)}.
\]  

(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,

\[
R_b c \frac{\lambda\mu}{\lambda\mu + (1 - \lambda)} + R_b cp\frac{(1 - \lambda)}{\lambda\mu + (1 - \lambda)} = Rc.
\]  

(13)

Thus, we derive the interest rate to the supplier, i.e.,

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

(14)

As shown, the risk premium decreases in \(\mu\). This is because when \(\mu\) 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 \(\bar{w}\). That is:

\[
w \geq \bar{w} = R_b c = \left[ 1 + \frac{(1 - \lambda)(1 - p)}{\lambda\mu + (1 - \lambda)p} \right] Rc.
\]  

(15)

Clearly, \(w\) decreases in \(\mu\). When \(\mu = 0\), i.e., no mis-classification, we have,

\[
w = \frac{1}{p} Rc.
\]  

(16)

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

\[
w = \frac{1}{\lambda + (1 - \lambda)p} Rc.
\]  

(17)

Depending on the range of \(w\), \(\bar{w}\) 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 \( \lambda + (1 - \lambda)p \leq Rc \), without Type-B technology, the bank only finances the firm when the signal is good (\( \theta = 1 \)).

In the following analysis, we assume the condition \( \lambda + (1 - \lambda)p \leq Rc \) 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 \( A \);
2. the impact of \( A \) on \( G \) is higher when a greater fraction of firms is good (large \( \lambda \)).

4.2. The Case with Type-B Technology

In this case, we have two signals: \( \theta \) and \( \theta_B \), where the latter one is from Type-B technology. The definition is similar to the ones without Type-B technology, i.e., when the supplier is good, we have:

\[
\Pr(\theta_B = 0 \mid \text{good}) = \mu_B, \tag{19}
\]

On the other hand, when the supplier’s bad, it cannot be mis-classified as good, i.e.,

\[
\Pr(\theta_B = 1 \mid \text{bad}) = 0. \tag{20}
\]

Under this case, we consider four scenarios depending on \( \theta_B \) and \( \theta \):

\[
\Pr(\text{good} \mid \theta = 1, \theta_B = 1) = \frac{\Pr(\text{good}, \theta = 1, \theta_B = 1)}{\Pr(\theta = 1, \theta_B = 1)} \tag{21}
= \frac{\Pr(\theta = 1 \mid \text{good})\Pr(\theta_B = 1 \mid \text{good})\Pr(\text{good})}{\Pr(\theta = 1, \theta_B = 1)} = 1. \tag{22}
\]

Similarly, \( \Pr(\text{good} \mid \theta = 1, \theta_B = 0) = \Pr(\text{good} \mid \theta = 0, \theta_B = 1) = 1 \). Finally,

\[
\Pr(\text{good} \mid \theta = 0, \theta_B = 0) = \frac{\Pr(\text{good}, \theta = 0, \theta_B = 0)}{\Pr(\theta = 0, \theta_B = 0)} = \frac{\lambda \mu \mu_B}{\lambda \mu \mu_B + (1 - \lambda)}. \tag{23}
\]

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

Combined, the fraction of firms who 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:

$$G_B = \lambda \mu \mu_B$$ (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 $A$,
2. the impact of $A$ on the financing gap $G$ is higher when a greater fraction of firms is good (greater $\lambda$).

### 5. Relationship between Type-A and Type-B technologies

Next, we consider the substitutability/complementary between these two types of FinTech investments. To do that, we compare $\frac{\partial G_B}{\partial A}$ and $\frac{\partial G}{\partial A}$:

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

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

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

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 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 $\frac{\partial \mu_B}{\partial A} \leq \frac{\partial \mu}{\partial A}$ 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, i.e., 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 piece of tamper-free evidence of the supplier’s qualification, which directly signal that the supplier’s performance risk is low. In this case, it becomes unnecessary to further invest in complex machine learning capability to further process this piece of straightforward information.

Symmetrically, we have the following condition under which the two types of FinTech is 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 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 to, through a digital payment system such as PayPal and AliPay, 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 can directly use in a transaction regardless of the bank’s Type-A investment (e.g., whether a delivery has passed inspection or custom);  
2. **Complicated** information that may require further processing by Type-A technology (e.g., new sources of historical payments and performance data)

As previously mentioned 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 via 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:

\[
\mu_B(0) = 0; \quad \frac{\partial \mu_B}{\partial A} = 0, \tag{30}
\]

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.

6. Investing in FinTech

In the previous section, in order to focus on the impact of FinTech in closing the financing gap, we treat FinTech as exogenous investment. In this section, we consider the optimal level of FinTech investment. We consider the investment decisions from two perspectives: the bank’s perspective, and the social planner’s perspective.

6.1. A Bank’s FinTech Investment

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

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

Thus, $A^*$ satisfies:

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

As $\mu$ 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 ($\lambda$).

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

$$A^*_B = \arg \max_A N(R - R_0)c\lambda(1 - \mu_B) - A \quad (33)$$

Thus, $A^*_B$ is determined by:

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

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 ($\lambda$).

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, that is:

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

$$\Pi^*_B = N(R - R_0)c\lambda(1 - \mu_B) - A^*_B \quad (36)$$

Using the Envelope Theorem, we have:

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

Therefore, as $B = \Pi^*_B - \Pi^*$, we have that:

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

That is, the impact of $\lambda$ on the Type-B investment threshold $B$ depends on whether the Type-B technology can reduce the financing gap. The relationship between $B$ 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, $B$ decreases in $\lambda$, $N$, and $(R - R_0)$. 

Electronic copy available at: https://ssrn.com/abstract=3465308
We next apply the exponential form in Equation (9) to obtain further insights:

**Proposition 9** When $\mu = ke^{-tA}$ and $\mu_B = k_BE^{-t_BA}$, under the bank’s profit maximization scenario, the optimal Type-A investments with and without Type-B technology are:

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

The corresponding financing gaps are:

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

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

$$\bar{B} = 1 + \ln\left(\frac{kN(R - R_0)c\lambda + \ln(t)}{t}\right) - \frac{1 + \ln[kk_BN(R - R_0)c\lambda + \ln(t + t_B)]}{t + t_B}. \quad (40)$$

Although the size and profit margin of a bank also matter, we especially interest in how the fraction of good firms, $\lambda$, affect the bank’s investment decision, as this represents market/country characteristics, and thereby can be used as an instruments by governments and/or non-profit organizations to motivate banks’ FinTech adoption. We again focus on the two extreme cases, the straightforward and the complicated cases, for illustration; see Figure 3 and Figure 4, respectively.

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 exhibits 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 so to avoid mis-classification 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 the 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.

6.2. The 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:

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

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

Similarly, with Type-B technology, the optimal Type-A investment $A^S_B$ is:

$$A^S_B = \arg \max_A N (R - R_0 + M) c\lambda(1 - \mu\mu_B) - A.$$ 

By solving these two problems, we have:

$$\frac{\partial \mu}{\partial A^S} = -\frac{1}{N(R - R_0 + M)c\lambda}.$$
\[ \mu \frac{\partial \mu_B}{\partial A^S_B} + \mu_B \frac{\partial \mu}{\partial A^S_B} = -\frac{1}{N(R-R_0+M)c\lambda}. \] (44)

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

The intuition behind the under-investment is clear: as the bank only enjoys a fraction of the benefit, it has no incentive to invest at the socially optimal level. Such under-investment offers rooms 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.

\[ \Pi^S = N(R-R_0+M)c\lambda(1-\mu) - A^S; \] (45)

\[ \Pi^S_B = N(R-R_0+M)c\lambda(1-\mu\mu_B) - A^S_B. \] (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 lowers the financing gap, \( \bar{B}^S \) decreases in \( \lambda, N, (R-R_0) \), and \( M \).

Regardless 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 addition insights, we resort to the exponential form in the following proposition.

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

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

The corresponding financing gaps are:

\[ G^S = \frac{1}{tN(R-R_0+M)c}; \quad G^S_B = \frac{1}{(t_B+t)N(R-R_0+M)c}. \] (47)

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

\[ \bar{B}^S = \frac{1 + \ln[kN(R-R_0+M)c\lambda] + \ln(t) - 1 + \ln[kk_BN(R-R_0+M)c\lambda] + \ln(t+t_B)}{t+t_B}. \] (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 \( G^*_S \leq G^S \)). With simple algebra, we can also see that \( G^S - G^S_S \leq G^*_B - G^* \), 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 under-invest 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:

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

(49)

We note that the under-investment 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 (e.g., the straightforward case), where \( t_B = 0 \), i.e., Type-A technology cannot improve the signal quality based on information collected by Type-B technology. In this case, the above proposition leads to:

\[ G^S = G^S_B. \]

(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:

\[ \bar{B} = \bar{B}^S = -\frac{\ln(k_B)}{t}. \]

(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 and 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 under-investment issue in Proposition 10, and such under-investment is more severe with high \( M \). In this case, governments should improve public data quality and enable data aggregation (e.g., credit scoring).

Finally, we note that banks’ under-investment in FinTech is double marginalization. To resolve such under-investment, one intuitive solution is for the bank to charge borrowers a fee for FinTech.
adoption. Such a solution, however, faces its only 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 profit, may have other unintended consequences, such as trade volume reduction, and adverse selection.

As a result, addressing the issue of under-investment 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 mis-aligned interests between financial institutes and financially stressed firms. Possible means include, but not limited to, tax benefits for financial institutes to adopt FinTech tools, technology assistance programs for
these financial institutes to learn and adopt new technologies, government platform for blockchain or AI, and provide protocols and standards for firm identity.

7. Conclusions

Financially constrained MSMEs rely on external finance to sustain and grow their business, and yet, these firms are also the ones receive the most trade finance rejections. Information asymmetry between these firms and financial institutes 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 (social optimal case).

By comparing the benchmark case with the case with FinTech, we find that both types of technologies help 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 the 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 depends on whether Type-B technology can lower the financing gap, and if the answer is positive, 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 under-invest in Type-A technology and/or Type-B technology. It is understandable that the bank only extract a portion of benefits from the FinTech investment, whereas the exporter firms extract the rest. Such double marginalization leads to banks’ under-investment in FinTech. Such under investment is more severe when the exporters’ margin is high. This calls for additional mechanisms, including private and public sectors collaboration on improving data quality, tax breaks, promoting digital standard, that help closing this gap.

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 along three directions. The first is at the exporter firm level. In our current model, the wholesale price and order quantity is exogenous. In the future,
we can consider to endogenize these two operational decisions for each firm. The second is at the
bank level. In our current setup, we consider that exporters will file their loan applications to the
bank. In practice, exporters can also choose the bank(s) that they want to do business. In the
presence of various transaction costs (e.g., long KYC 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 policymaker’s perspective, we can examine the
effectiveness of various incentive schemes to promote FinTech adoptions and investment, thereby
improving social welfare.

Acknowledgments
This paper was prepared as background material for the Asia-Pacific Trade Facilitation Report 2019 with
a theme chapter on “Bridging Trade Finance Gaps through Technology.” The authors thank participants
in the Asian Development Bank ERCD-PSOD Joint Seminar on trade finance and technology, especially
Yasuyuki Sawada, Cyn-Young Park, and Steven Beck, for their valuable inputs.

References
Antras, P., C F. Foley. 2015. Poultry in motion: a study of international trade finance practices. Journal of
Political Economy 123(4) 853–901.
Biais, B., C. Gollier. 1997. Trade credit and credit rationing. Review of Financial Studies 10(4) 903–937.
Buchak, G., G. Matvos, T. Piskorski, A. Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow
banks. Journal of Financial Economics 130(3) 453–483.
Burkart, M., T. Ellingsen. 2004. In-kind finance: A theory of trade credit. American Economic Review 94(3)
569–590.
Chod, J., E. Lyandres, S. A. Yang. 2019. Trade credit and supplier competition. Journal of Financial
Economics 131(2) 484–505.
Di Caprio, A, K. Kim, S. Beck. 2017. 2017 Trade Finance Gaps, Growth, and Jobs Survey. URL https://
www.adb.org/sites/default/files/publication/359631/adb-briefs-83.pdf. Accessed at April 4, 2019.
Foley, C.F., M. Johnson, D Lane. 2010. Note on international trade finance. Harvard Business School,
Industry and Background Note.
Hoefele, A., T. Schmidt-Eisenlohr, Z. Yu. 2016. Payment choice in international trade: Theory and evidence
from cross-country firm-level data. Canadian Journal of Economics 49(1) 296–319.
HSBC. 2018. HSBC and ING carry out blockchain trade finance transaction. URL https://www.finextra.
com/pressarticle/76237/hsbc-and-ing-carry-out-blockchain-trade-finance-transaction.
Accessed at April 3, 2019.
Hu, M., Q. Qian, S.A. Yang. 2018. Financial Pooling in a Supply Chain. Available at SSRN.

Klapper, L. 2006. The role of factoring for financing small and medium enterprises. Journal of Banking and Finance 30(11) 3111–3130.

Lee, H.H., J. Zhou, J. Wang. 2018. Trade credit financing under competition and its impact on firm performance in supply chains. Manufacturing & Service Operations Management 20(1) 36–52.

Lee, H.L., C.S. Tang, S.A. Yang, Y Zhang. 2019. Milestone-based Supply Chain Finance. Working Paper.

Manova, K. 2012. Credit constraints, heterogeneous firms, and international trade. Review of Economic Studies 80(2) 711–744.

Maskey, S. 2018. How Artificial Intelligence Is Helping Financial Institutions? URL https://www.forbes.com/sites/forbestechcouncil/2018/12/05/how-artificial-intelligence-is-helping-financial-institutions/#4f5d3d8d460a. Accessed at April 4, 2019.

Morris, N. 2018. Trade finance blockchain race is about to start. URL https://www.ledgerinsights.com/wetrade-trade-finance-blockchain-race/. Accessed at April 4, 2019.

Niepmann, F., T. Schmidt-Eisenlohr. 2017a. International trade, risk and the role of banks. Journal of International Economics 107 111–126.

Niepmann, F., T. Schmidt-Eisenlohr. 2017b. No guarantees, no trade: How banks affect export patterns. Journal of International Economics 108 338–350.

Philippon, T. 2015. Has the us finance industry become less efficient? on the theory and measurement of financial intermediation. American Economic Review 105(4) 1408–38.

Philippon, T. 2016. The fintech opportunity. Tech. rep., National Bureau of Economic Research.

Reindorp, M., F. Tanrisever, A. Lange. 2018. Purchase order financing: Credit, commitment, and supply chain consequences. Operations Research 66(5) 1287–1303.

Schmidt-Eisenlohr, T. 2013. Towards a theory of trade finance. Journal of International Economics 91(1) 96–112.

Tang, C. S, S. A. Yang, J. Wu. 2018. Sourcing from suppliers with financial constraints and performance risk. Manufacturing & Service Operations Management 20(1) 70–84.

Viswanatha, A., B. Wolf. 2012. HSBC to pay $1.9 billion U.S. fine in money-laundering case. URL https://www.reuters.com/article/us-hsbc-probe/hsbc-to-pay-1-9-billion-u-s-fine-in-money-laundering-case-idUSBRE8BA05M20121211. Accessed at April 5, 2019.

Wass, S. 2019. Banks start using we.trade blockchain platform for open account trade finance. URL https://www.gtreview.com/news/fintech/banks-start-using-we-trade-blockchain-platform-for-open-account-trade-finance/. Accessed at April 4, 2019.

Electronic copy available at: https://ssrn.com/abstract=3465308
Yang, S. A., N. Bakshi, C. Chen. 2019. Trade credit insurance: Operational value and contract choice. *Available at SSRN 2735907*.

Yang, S. A., J. R. Birge. 2018. Trade credit, risk sharing, and inventory financing portfolios. *Management Science* **64**(8) 3667–3689.
Appendix A: FinTech Investment when the 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 (9). In this appendix, we replace the exponential form by the following polynomial functional form:

$$\mu = k(1 + A)^{-1}; \quad \mu_B = k_B.$$  \hspace{1cm} (A.1)

The following proposition reveals that the main insights remain unchanged.

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

1. under the bank’s profit maximization scenario, the optimal Type-A investments with and without Type-B technology are:

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

**The corresponding financing gaps are:**

$$G^* = (k\lambda)^{\frac{1}{1+t}} [N(t(R - R_0)c]^{\frac{1}{1+t}}; \quad G_B^* = (k_{k}\lambda)^{\frac{1}{1+t}} [N(t(R - R_0)c]^{\frac{1}{1+t}}.$$ \hspace{1cm} (A.2)

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

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

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

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

**The corresponding financing gaps are:**

$$G^S = (k\lambda)^{\frac{1}{1+t}} [N(t(R - R_0 + M)c]^{\frac{1}{1+t}}; \quad G_B^S = (k_{k}\lambda)^{\frac{1}{1+t}} [N(t(R - R_0 + M)c]^{\frac{1}{1+t}}.$$ \hspace{1cm} (A.4)

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

$$B^S = [1 - (k_B)]^{\frac{1}{1+t}} \left( t^{\frac{1}{1+t}} + t^{-\frac{1}{1+t}} \right) [kN(R - R_0 + M)c\lambda]^{\frac{1}{1+t}}.$$ \hspace{1cm} (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, i.e., $\partial\mu_B/\partial A = 0$, we still find that Type-B technology helps further close the financing gap, i.e., $G^* > G_B^*$ and $G^S > G_B^S$. This observation indeed indicates the importance to estimate a right form.

Nonetheless, we note that

$$B^S - B = [k_B]^{\frac{1}{1+t}} - 1 \left( t^{\frac{1}{1+t}} + t^{-\frac{1}{1+t}} \right) [kN(R - R_0)c\lambda]^{\frac{1}{1+t}} \left[ 1 - \left( 1 + \frac{M}{R - R_0} \right)^{\frac{1}{1+t}} \right] > 0.$$ \hspace{1cm} (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 B: Proofs

Proof of Propositions 9 and 12 Under the bank profit maximization scenario, substituting $\mu = ke^{-1A}$ and $\mu_B = k_B e^{-b A}$ into $\Pi^*$, $\Pi_B^*$, we have:

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

Thus, the resulting $\mu$ and $\mu_B$ are:

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

which leads to the financing gaps as in the proposition.

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

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

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

Therefore, $\bar{B}$ follows:

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

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

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

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

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

And the financing gaps are:

$$G^s = \frac{1}{tN(R - R_0 + M)c}; \quad G_B^s = \frac{1}{(t_B + t)(R - R_0 + M)c}.$$ 

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 $\mu = k(1 + A)^{-1}$ and $\mu_B = k_B$ into $\Pi^*$, we have:

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

Therefore, we can derive,

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

and the resulting signal quality $\mu$ is:

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

The corresponding financing gap is:

$$G^* = (k\lambda)^{\frac{1}{1+\lambda}}[Nt(R - R_0)c]^{\frac{1}{1+\lambda}}.$$
The bank’s profit is:

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

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

$$A^*_B = [kk_BTN(R - R_0)c\lambda]^{\frac{1}{1+T}} - 1; \quad (B.13)$$
$$\mu(A^*_B) = k[kk_BTN(R - R_0)c\lambda]^{\frac{1}{1+T}}; \quad (B.14)$$
$$G^*_B = (kk_B\lambda)^{\frac{1}{1+T}} [Nt(R - R_0)c]^{\frac{1}{1+T}}; \text{ and} \quad (B.15)$$
$$\Pi^*_B = N(R - R_0)c\lambda - \left( t^{\frac{1}{1+T}} + t^{\frac{1}{1+T}} \right) [kk_BTN(R - R_0)c\lambda]^{\frac{1}{1+T}} + 1. \quad (B.16)$$

By comparing $\Pi^*$ and $\Pi^*_B$, we have:

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

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