How the use of alternative information in risk management fintech platforms influences SME lending: a qualitative case study

Jie Yan
Accounting and Information Systems, The University of Texas at El Paso, El Paso, Texas, USA

Received 27 August 2023
Revised 27 November 2023
Accepted 15 February 2024

Abstract

Purpose – The purpose of the study is to examine the use of alternative information in bank lending to small and medium enterprises (SMEs). Understanding alternative information and its use in bank lending to SMEs is important because it has become a growing part of the future of SME finance. The results and findings of my study not only enrich the finance literature but, more importantly, also address the use of Fintech in the risk management of SME lending, a new and complex problem that is specific to both the information technology and finance field.

Design/methodology/approach – To answer the research question, the author used a case study approach that relies upon qualitative data and analysis. By iterating between the existing literature, theoretical pieces and empirical findings, the author explain and interpret in detail how the use of alternative information impacts loan outcomes and develop insights to guide future research.

Findings – The case is outlined in two time periods including the prepartnership period and the postpartnership period. It highlights the establishment of a partnership between LoanBank and FintechInc (pseudonym), aimed at SME-focused Fintech lending. The findings underscore how the partnership has enabled a mutually beneficial situation where LoanBank and FintechInc leverage each other's strengths to provide efficient and effective lending services. The adoption of alternative information in the risk management Fintech (RMF) platform of FintechInc has transformed LoanBank's lending processes, showcasing how technological innovations can enhance SME lending practices.

Originality/value – The study's originality mainly lies in the three detailed insights regarding alternative information's impact on SME lending: information, platform properties and financial inclusion. The information part demonstrates that RMF platforms expand the information used for lending decisions, shifting from traditional hard and soft data to incorporating various alternative information sources. The platform properties part suggests that location, openness and technology also play a pivotal role in shaping lending outcomes. Finally, the financial inclusion part proposes that the use of alternative information has the potential to improve financial inclusion and offer better credit terms to previously underserved borrowers.

Keywords Fintech platforms, Risk management, Alternative information, Credit evaluation, Financial inclusion, Case study

Paper type Case study

1. Introduction

Fintech, as an umbrella term, encompasses innovative financial solutions and business models enabled by information technology (Puschmann, 2017). It is often used to describe startups that deliver such solutions and models while also including the incumbent financial services providers like banks and insurers. Even as Fintech disrupts existing financial industry structures and revolutionizes how existing players create and deliver products and services, it also creates significant privacy, regulatory and law-enforcement challenges

Qualitative Research in Financial Markets
© Emerald Publishing Limited
1755-4179
DOI 10.1108/QRFM-08-2023-0198

(Allen *et al.*, 2018). Examples of innovations that are central to Fintech today include blockchain, digital trading systems, digital banking and credit, peer-to-peer lending, crowdfunding and mobile payment systems (Philippon, 2016).

This study focuses on risk management Fintech (RMF) platforms, a key enabler for digital banking and credit, peer-to-peer lending and crowdfunding. RMF platforms refer to online platforms that use mobile Internet big data, artificial intelligence technology and/or professional risk control experience to provide online and offline financial institutions with intelligent decision-making and system solutions (Allen *et al.*, 2018; Dhar and Stein, 2017). The application areas of RMF platforms span the complete personal and business financing life cycle including risk control, risk pricing, quota strategy and asset valuation (Gomber *et al.*, 2018). In digital banking and credit, for example, RMF platforms can help produce better risk reporting, enabling bank control functions to adjust prioritization based on market/customer condition changes and managers to oversee and determine intervention points (Jung *et al.*, 2018; Puschmann, 2017). RMF platforms have been adopted by both Fintech lenders and banks in various personal and business products and services. The present study is interested in its application in bank lending to small and medium enterprises (SMEs).

SMEs' access to bank credit – i.e. loan availability and loan price – has become an ongoing research stream in financial studies (see Alessandrini *et al.*, 2009; Carbó-Valverde *et al.*, 2009 for recent reviews). With the rise of Fintech, both practitioners and scholars have argued that the development of RMF platforms is in part a market response to SME lending and would, in the long run, help plug the gaps in the supply of bank credit to SMEs (Degryse *et al.*, 2018; Härle *et al.*, 2015). This is primarily because RMF platforms hold the potential to change the nature of SME lending from an emphasis on strict ex ante screening and costly information production and use to frequent ex post monitoring and quick intervention (Degryse *et al.*, 2018; Jagtiani and Lemieux, 2016). These practical considerations motivated me to examine the impact of RMF platforms on bank lending to SMEs. In the present study, I seek to contribute to the existing Fintech literature by focusing on *alternative information* and exploring how its use in RMF platforms impacts SMEs' access to bank credit.

Alternative information in banking generally refers to information that is gathered from nontraditional information (or data) sources and is not typically included in traditional credit approval criteria (Liberti and Petersen, 2019). Specifically, traditional information in banking largely relates to firm and relationship characteristics (Berger and Udell, 1995; Cassar *et al.*, 2015). For example, information on a business's financial performance (revenue, profits and liabilities) and accounting reports (credit scores, trade credit and accounts receivable) is often used to represent firm characteristics. The number of years that current owners have owned the business and conducted business with their current bank is often used to represent the strength of a lender-borrower relationship (i.e. relationship characteristics). Through a strong lender-borrower relationship, a lender can learn more about the business (e.g. the quality of management and operations). In contrast, alternative information may include any structured and unstructured information (or data) that are not normally used to represent firm and relationship characteristics and in making lending decisions. Examples of such unstructured information include social media, public records in texts and founder/owner's personal data; and examples of structured information include turnover, shipping and other transaction data. Alternative information, combined with traditional information (if available), has been increasingly used by lenders, especially nonbank lenders (financial institutions that do not accept deposits) and Fintech startups, to compensate for information asymmetries in SME lending, as I will discuss in more detail to follow. In this study, I am particularly interested in the use of alternative information in RMF platforms and exploring its impact on SME lending outcomes.

The paper proceeds as follows. First, I will review related literature on the use of information technology in SME lending and how it has been impacted by the use of alternative information in RMF platforms. Then I will detail the data, method and findings of the case study, followed by an interpretation of how the use of alternative information impacts SME lending. The interpretation consists of three major insights regarding information, platform properties and financial inclusion. I conclude the paper by discussing the implications for the research and practice of RMF platforms. This includes exploring how RMF platforms use diverse data sources to assess borrower creditworthiness and facilitate more accurate risk evaluation and lending decisions, identifying critical success factors such as data quality, analytics and partnerships that enhance RMF platform efficiency and emphasizing the need for collaboration, regulation and consumer advocacy to ensure fair lending practices in Fintech.

2. Theoretical background and literature

2.1 Hard and soft information and information technology in small and medium enterprises lending

Acquiring traditional information about SMEs, most of which are private and not required to disclose much information, has historically been difficult for lenders (Petersen and Rajan, 1994). SME insiders generally have better information on the firm's financial performance and default risk than lenders. As a result, information asymmetries – i.e. one party has more or better information than the other – tend to be large in SMEs (Saifurrahman and Kassim, 2023; Cassar *et al.*, 2015; Jaffee and Russell, 1976). The resulting information risk has influenced SME lending decisions (Berger and Udell, 1995, 2006).

To minimize the information asymmetries, lenders have typically relied on decision cues taking the form of both quantitative (or "hard") and qualitative (or "soft") information. Hard information is quantitative, often recorded as numbers and, therefore, can be thought of as a numeric index (Liberti and Petersen, 2019). Examples of hard information include income tax, employment costs and property value. Such hard information does not depend upon the context under which it was collected and can be collected without the assistance of a human data collector (Godbillon-Camus and Godlewski, 2005; Liberti and Petersen, 2019). By contrast, soft information is qualitative, often communicated as text and depends on the context reference. Examples of soft information include product ideas, management commentary, senior management's character, etc. Although soft information can always be hardened into a numeric index, doing so often results in a loss of information or context. For example, an index of 6 (from 1 to 10) on how creative an idea is can be interpreted differently by different people or systems. Because of this, soft information needs to be collected in person and the collector is also part of the information, especially when the collector is the decision maker (Liberti and Petersen, 2019). Compared with hard information, soft information has higher transaction costs, being less standardized and difficult to store and maintain (Frame *et al.*, 2001).

The above examples of decision cues in the forms of hard and soft information have been combined and traded off by lenders to reduce information asymmetries during SME lending (Cassar *et al.*, 2015; Saha *et al.*, 2016). The use of these hard and soft information decision cues and resulting compensation for information asymmetries has helped lenders to receive more precise signals in terms of SME profile. It thereby helps lenders to distinguish whether an SME can be qualified as a low-risk borrower.

On the other hand, the diffusion and use of information technology in the financial sector over the last decades have affected how financial institutions obtain information cues and compensate for information asymmetries in lending. From the hard information perspective, the development and use of information and communications technology has resulted in increased availability of processed hard information (e.g. financial histories and results from credit scoring). This allows less personal interaction between the lenders and borrowers (Mishkin and Strahan, 1999). Hard information can be collected automatically and has become systematic and reliable, reducing the costs of credit appraisal and monitoring at a distance (Petersen and Rajan, 2002). This further allows the timely intervention of lenders if borrower moral hazard is observed.

From the soft information perspective, however, the growing use of information technology has led to decreasing soft information captured by close personal contact and relationships with businesses (Berger and Udell, 1995; Mishkin and Strahan, 1999). This is not only because of the increased availability and advantages of hard information but also because of the tendency of financial institutions to build business models that depend on automated decisions rather than decisions made by individuals (Liberti and Petersen, 2019). Even banks whose loans are more relationship-based, tend to quantify the soft relationship information (Giannetti *et al.*, 2017; Hoberg and Phillips, 2016). This is especially true for many nonbank lenders who have involved more technologies and fewer people in loan originations and monitoring.

2.2 Alternative information in risk management Fintech platforms

The rapid emergence of Fintech, RMF platforms in particular, has further increased the availability and timeliness of hard information. Moreover, and more importantly, it enables the Fintech companies to better capture and harden soft information. The result is the use of a broad variety of decision cues, namely, *alternative information*, by RMF platforms to compensate for the lack and unavailability of traditional information in personal and business financing. For example, as one type of alternative information, personal characteristics such as physical attractiveness have been used by RMF platforms in risk assessment. Duarte *et al.* (2012) revealed that borrowers are likely to receive a lower loan price when they are perceived to be more trustworthy, based on their online pictures. Also, using machine learning and psychology text-mining techniques, RMF platforms are able to uncover linguistic tip-offs (e.g. deception and clarity) in the narratives of managers/owners that may inform credit risk. Herzenstein *et al.* (2011), for instance, found that the narratives of owners who claim they themselves are trustworthy increase the probability of receiving a loan.

Furthermore, in the world of big data and social networks, RMF platforms often look for and use alternative information related to an individual's social circles to infer creditworthiness (e.g. Lin *et al.*, 2013; Lu *et al.*, 2012). Lin *et al.* (2013), for example, found that the credit quality of one's friends is an informative signal of the credit quality of oneself. A lender tends to obtain higher loan returns if the lender is also a friend of the borrower and endorses the loan (Lin *et al.*, 2013). Some local economic information, such as house price data (Ramcharan and Crowe, 2013), unemployment rates (Bertsch *et al.*, 2016) and percentage of minority residents (Agarwal *et al.*, 2017), has also been used as alternative information in RMF platforms. Table 1 summarizes my discussion thus far and Table 2 further summarizes some other related studies on the use of alternative information in RMF.

Although existing research provides valuable insights into the use of alternative information in RMF platforms, as discussed above, it tends to focus on one particular type of alternative information (Table 2) and thereby falls short of explaining *how* alternative information has affected personal or business financing. Understanding alternative information and its use in bank lending to SMEs is important because it has become a growing part of the future of SME finance (Dhar and Stein, 2017; Owens and Wilhelm, 2017). Drawing on a case study, I seek to answer the following question:

	Hard information	Soft information
Traditional information	*Examples:* Financial and accounting statements (if available), income tax, employment costs *In relation to technology*: Becomes more available, timely and useful with the use of IT	*Examples*: Product ideas, management commentary, senior management's character *In relation to technology*: Depends less on IT but more on the length and strength of an existing borrower-lender relationship
Alternative information	*Examples*: Local economic information, physical appearance, number of social media friends and their credit scores *In relation to technology*: Requires the use of Fintech, RMF platforms in particular, to capture and process the data	*Examples*: linguistic tip-offs, online product reviews, social media texts *In relation to technology*: Depends primarily on the extent to which the information can be captured and hardened by the use of Fintech and RMF platforms

Source: Created by the author

Table 1. In relation to technology: traditional and alternative information

Study	Context	Focus	Key finding
Ge *et al.* (2017)	Online peer-to-peer lending	The impact of borrowers' self-disclosed social media information on their default probability	Borrowers who have more substantial social media presence (e.g. more friends and more messages posted) are less likely to default
Lin *et al.* (2013)	Online peer-to-peer lending	The use of online friendships of borrowers as signals of credit quality	Friendships increase the probability of successful funding, lower interest rates on funded loans and are associated with lower ex post default rates
Di Maggio and Yao (2021)	Fintech lenders versus bank lenders in consumer lending	Whether or not Fintech lenders have eased credit access for borrowers underserved by traditional banking	Fintech borrowers, versus individuals borrowing from banks, earn more, live in higher income neighborhoods, are on average younger and more likely to be professionals
Riggins and Weber (2017)	Online peer-to-peer lending	The impact of information asymmetries and identification bias in peer-to-peer lending	Distant lenders who do not have adequate information about local business and loan conditions tend to make funding decisions based on identification biases
Xu and Chau (2018)	Online peer-to-peer lending	The use of information from different sources to reduce uncertainty caused by information asymmetries	The quality of the information disclosed in borrowers' responses to lenders' comments (positive or negative) on loan applications affects funding outcomes
Alyakoob (2020)	Online peer-to-peer lending	The role of local competition in driving strategic responses of the traditional banking markets to the growth of online peer-to-peer lending	The number of local lending institutions (as a proxy for the local market competition) has a significant impact on the prepayment behavior of peer-to-peer borrowers

Source: Created by the author

Table 2. Related studies

Q1. How does the use of alternative information in RMF platforms influence SME lending outcomes?

3. Method

To answer my research question, I used a single case study approach. I obtained access to qualitative data by collaborating with a leading Fintech company, FintechInc (a pseudonym), in China. FintechInc's RMF platform covers the loan life cycle including prequalification and application, underwriting analysis, monitoring and collections. In September 2018, FintechInc received the "Best Innovative Award for Risk Management in Retail Banking" from the China Retail Banking Innovation International Summit. FintechInc does not originate and fund loans itself but partners with LoanBank, a pseudonym, to provide algorithm-based systems and solutions. LoanBank is a joint-stock commercial bank that serves its customers through a branch/subbranch network across the major cities in China. Such a partnership between traditional banks and external Fintech companies has become a new business model of SME-focused Fintech lending (Owens and Wilhelm, 2017).

3.1 Data collection and analysis

I conducted both face-to-face and computer-mediated interviews from August 2020 to February 2022 with the product managers of FintechInc (see Appendix 1 for details). The project managers were in charge of the development of the risk management platform for LoanBank and were willing to participate in the interviews. Apart from the interview data, I collected data from other sources including internal documents of the lending processes of LoanBank, training and project documents of FintechInc and external news and blogs of both LoanBank and FintechInc. Many training documents and articles on FintechInc's risk management technology and products were also available on the company's website for the public to access and download. Table 3 further details the data I have collected and analyzed in this study.

My qualitative data analyses involved a process of three stages. First, I conducted *open coding* by reading the text files transcribed from the interview recordings and selecting open codes that relate to the use of alternative information in FintechInc's RMF platforms and its impact on the loan processes of LoanBank. A total of 87 open codes emerged and I grouped similar codes into categories between which I sought to create initial relationships. Based on

	Interviews	Internal documents	External press
Description	Face-to-face (December 2020 to January 2021): 4 (about 1–3 h each) Mediated on WeChat [3] (August 2020 to February 2022): 9 (about 30–60 min each)	Business lending processes of LoanBank: 1 Internal credit ratings of LoanBank: 1 Training documents/articles on FintechInc's risk management technology and products: 31 Project documents of FintechInc: 2	News of LoanBank: 2 News and blogs of FintechInc: 7
Total data items	13 (Qualitative)	35 (Qualitative and quantitative)	9 (Qualitative)
Reliance on evidence	High	Medium	Low

Source: Created by the author

Table 3.
Data collection

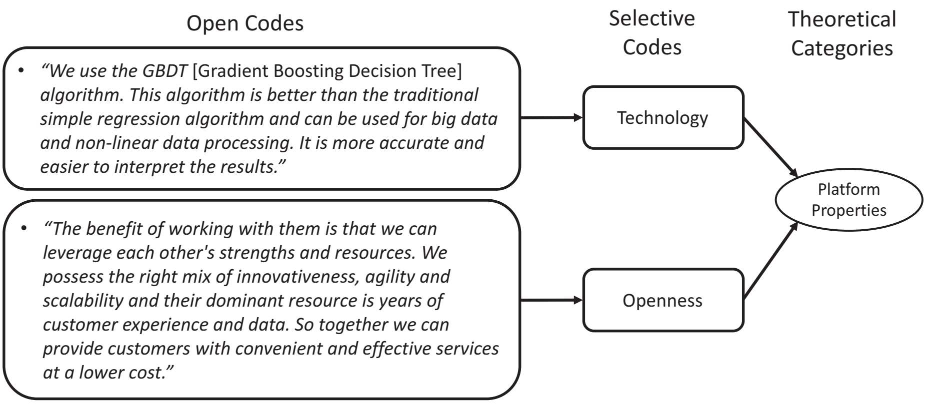
my research question and these open coding categories, I then used *selective coding* to form higher-level selective codes. These selective codes include credit ratings (LoanBank), loan availability (LoanBank), loan price (LoanBank), data and information (FintechInc and LoanBank), openness and collaboration (FintechInc and LoanBank), data modeling and technology (FintechInc), risk ratings (FintechInc), relationship (SMEs and LoanBank) and firm characteristics (SMEs). After iterating between these selective codes and the literature and theoretical background, I further developed theoretical categories (i.e. *theoretical coding*) including *information*, *platform properties* and *financial inclusion*. These theoretical categories then served as guidance to help me code and analyze the case further (Urquhart, 2012). Figure 1 presents examples to help demonstrate the qualitative data analysis process.

4. Findings

In December 2017, LoanBank and FintechInc established a partnership for SME-focused Fintech lending. Through the partnership, LoanBank's loan officers can perform their own deliberation and discussion using the risk evaluation results provided by FintechInc's RMF platforms and then make loan disbursement decisions and determine the loan price within a very short period of time. As the manager of standardized risk control explains: "They [LoanBank] want to make a decision within 7 working days for applications with a loan amount of less than 10 million [Yuan]." FintechInc, on the other hand, can avoid the cumbersome and bureaucratic procedure for obtaining a lending license by having LoanBank originate the loans. Such a partnership provides SMEs with convenient and fast financial services while improving efficiency and reducing the lending cost of LoanBank. The quote below from FintechInc's product manager of customized risk control further explains such win-win situations:

> The benefit of working with them is that we can leverage each other's strengths and resources. We possess the right mix of innovativeness, agility and scalability and their dominant resource is years of customer experience and data. So together we can provide customers with convenient and effective services at a lower cost.

To understand how the use of alternative information in RMF platforms impacts SME lending and helps achieve these outcomes, the case findings below describe how the



Source: Created by the author

Figure 1. Data analysis example

information is produced and used for evaluating risk and making decisions before and after the partnership.

4.1 Prepartnership period

During the second half of 2002, LoanBank began implementing the reform aimed to augment their competitiveness in the day of imminent foreign competition (as China joined the World Trade Organization in December 2001). Decentralization was one of the central themes of this reform. Compared to the old regime where each step of the lending process (e.g. investigation, verification, approval and monitoring) was conducted by a group of people, decentralization imposed greater responsibilities on individual loan officers. They must review and sign off on documents produced at each lending step and can be held liable for bad loans resulting from reckless and inaccurate internal ratings.

LoanBank's internal credit rating was the subjective rating of an SME by the branches/subbranches' loan officers. It ranged from one to eight with one representing the lowest credit quality and eight representing the highest credit quality. LoanBank's internal rating process was based on the soft and hard information of the SMEs collected by the loan officers. This information was mainly traditional and reflected the past and recent performance of the SMEs including revenue, profitability and forecasted earnings growth (if available). As the product manager of end-to-end online credit explains:

> Every company needs to fill out a loan application form to explain their financial performance and status for at least one year prior to the loan application. They also need to sign a power of attorney agreeing to access their credit history and information.

For those SMEs who had acquired loans before, loan officers also evaluated their repayment records. Some traditional soft/hard information was not publicly available and verifiable. Loan officers therefore often needed to talk with the owners, partners, customers and guarantors (if any) of the SMEs to proceed with the rating. The product manager also explains that: "There must be personal interest in this, so the score cannot be completely objective. Yet they have to sign the final report, accountable for bad loans."

Because these internal credit scores were assigned by the loan officers based on their own loan assessment using primarily traditional information, the resulting credit ratings of SMEs were largely associated with the firm and relationship characteristics such as revenue, profit, debt and the length/strength of an existing SME–LoanBank relationship. As the product manager of custom modeling explains: "We have modeled their previous loan data, and a large part of their credit ratings should be related to the company's financial performance and historical application records."

4.2 Postpartnership period

Partnering with FintechInc enables LoanBank to outsource the work of loan investigation, verification and monitoring to FintechInc and only focus on making loan decisions and taking actions accordingly. The use of FintechInc's RMF platform helps LoanBank improve its efficiency while also reducing the costs of making SME loans. The key modules of this customized platform are the enterprise risk model (ERM) and operation monitoring model (OMM). Both models are developed for SME lending and are able to conduct credit analysis and business profiling for risk management. They retrieve data from a data mart that gathers data from three sources: real-time data, internal data aggregators and external data vendors. The product manager of customized risk control explains the function of the data mart:

> Real-time data is information about the status of operations of the business. The operation monitoring module on the platform uses this information to monitor before and after the loan. The data accumulated on the platform is mainly managed by our internal data aggregators and database. For example, some people and companies have generated information and records on multiple platforms and products, and the results will be centralized to our internal database for modeling and analysis. We also have a large amount of external data from our data vendors such as Alibaba's various B2C, B2B trading platforms. These data include historical credit records, customer reviews and transaction details.

While relying on the same data mart, ERM and OMM retrieve different types of data for different purposes. ERM is focused on initial credit quality evaluation for new customer screening. It mainly uses the credit information of the business from internal data aggregators and/or external data vendors. This credit information consists of traditional information such as financial statements and relationships with the lenders. It also includes various alternative information such as the Chinese government's data on registered businesses, owners/managers' experience, major business address changes, tax-related issues and news/social media reports; see Appendix 2 for a detailed list of the alternative information. As the product manager of custom modeling further explains:

> This enterprise risk module will also link personal credit to the enterprise. Once changes are found, the variable parameters of the model are automatically adjusted. We use the GBDT [Gradient Boosting Decision Tree] algorithm. This algorithm is better than the traditional simple regression algorithm and can be used for big data and non-linear data processing. It is more accurate and easier to interpret the results.

Compared to ERM, OMM is mainly used for preloan and postloan monitoring of business operating conditions and relies more on real-time data. During the loan monitoring, for example, OMM would monitor and analyze location-based service data generated by the mobile devices within the location of an SME. If the SME is in the restaurant or retail industry, for instance, the historical changes in the number of mobile devices should reflect the historical trends of the location's passenger traffic and hence be a good informative signal of the operating conditions of the SME. Also, OMM would upgrade or downgrade the operating condition of an SME if the real-time data and/or data from external partners' platforms indicate significant changes in sales activities and payment records.

As the output of the model, both ERM and OMM generate a standardized risk rating for each SME. Each rating ranges from one to four representing low, average, above average and high risk, respectively. Additionally, the platform will consolidate a Corporate Panorama Report (CPR) for each SME. The CPR not only highlights the risk ratings that illustrate the overall risk profile of an SME but also summarizes the information analyzed by FintechInc over a specific time frame. Appendix 2 also presents a CPR template as an example to highlight the various types of alternative information used by the platform. This CPR is then used by LoanBank's loan officers and branch presidents for loan approval and terms. The product manager of standardized risk control highlights the impact of the use of alternative information on credit ratings:

> Both modules will score companies with their own data. Our modeling process is not comparable to their [LoanBank] manual scoring. They only use traditional customer data. We use more data for real-time processing. The results are very fast and objective. But their customer data is still very useful to us.

5. Discussion

The purpose of the present study is to understand how the use of alternative information in RMF platforms impacts SME lending outcomes. By iterating between existing literature, theoretical pieces and my empirical findings, I developed Figure 2. It summarizes three insights regarding alternative information's impact on SME lending: *information*, *platform properties* and *financial inclusion*. Below I discuss each of these in detail.

5.1 Information

I first suggest that at the heart of RMF platforms' impact on SME lending is *what and how* information is used for decision-making. My study shows that when risk assessment is conducted by loan officers, the resulting credit ratings largely depend on the traditional hard and soft information such as distance and firm and relationship characteristics that are accessible to them. Yet this type of information becomes less relevant to the credit risk and is given relatively less weight in making lending decisions when the RMF platform is used. This is because a large variety and amount of alternative information is added to the risk assessment process to compensate for the lack of traditional information. It is clear that under RMF platforms, the information upon which lenders make decisions has expanded.

Nevertheless, as an explorative case study, I am unable to examine further the differential role of alternative information in SME-focused Fintech lending by categorizing them into different types. In other words, what is still unclear is how much predictive value each type of alternative information will add to credit evaluation. Does traditional information still outperform alternative information in risk assessment? Are traditional information and alternative information overall complements or substitutes? Although the use of alternative information would help RMF platforms paint a more accurate and fuller picture of a borrower's creditworthiness, how and to what extent traditional information and alternative information should be combined for better credit and loan decisions deserves future research.

Moreover, as noted earlier, RMF platforms tend to be developed on the concept of hardening soft information. FintechInc is no exception. Although the information was expanded resulting from the use of alternative information, all the soft information had to be quantified. FintechInc's RMF platform needs and is able to condense various types of texts (e.g. social media, opinion columns and news stories) into numerical indexes for risk profiling. I suggest that such hardening of soft information would impact loan outcomes. On the one hand, it would lead to a loss of context information, as discussed earlier. On the other hand, borrowers and market participants may manipulate the inputs of a platform that is based purely on hard information in their own interest (Diamond *et al.*, 2018). How to restrict such behavior and deal with the challenges raised by hardening soft information, therefore deserves future research as well.

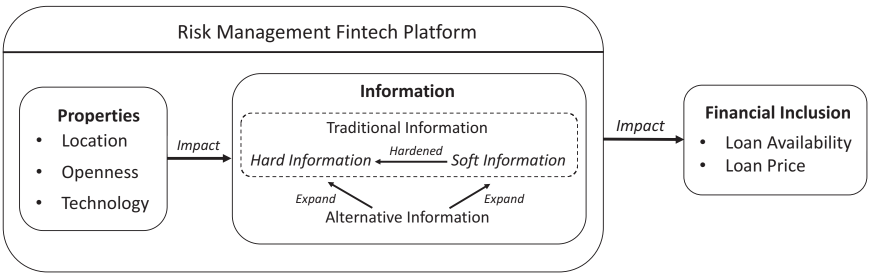


Figure 2. How alternative information and RMF platform impact SME lending

Source: Created by the author

5.2 Platform properties

Although the use of alternative information would play a critical role in determining loan outcomes, I suggest they also hinge on platform properties, including *location*, *openness* and *technology*. Location is important to consider because different regions and countries have different levels of Fintech development, regulations and cultures. Taking China in this study as an example, it not only enjoyed the late-mover advantage but also has better-integrated growth of technology, finance and real-life needs. A strong trial-and-effort culture in China has also facilitated aggressive investments in Fintech innovations (Ngai *et al.*, 2016). The result is that Fintech development and implementations in China occur much faster than in many developed countries such as the UK and the USA (Chen, 2016). This would enable multiple Fintech companies to work together for data and platform sharing, expanding the information upon which lenders could conduct risk assessments and make loan decisions [1].

Openness relates to who has access to the proprietary information developed and/or acquired by Fintech companies. It may run on a spectrum from limited access only to Fintech companies themselves to fully open to all business partners. In this study, the partnership between FintechInc and LoanBank allows the platform model results to be shared between the two parties. This high trust and relationship would allow LoanBank to leverage FintechInc's platform to process SME loans efficiently and effectively. Apart from a partnership, banks can obtain access to RMF platforms and information in other ways, such as making equity investments in or licensing/buying technology from the Fintech companies (Navaretti *et al.*, 2017). These different business models often lead to different levels of access to platform information and models and as a result, would have different effects on lending outcomes (see Jagtiani and Lemieux, 2016; Rudegeair *et al.*, 2015).

Technology in RMF platforms refers to various machine learning algorithms and models that both capture and generate vast amounts of information for decision-making. FintechInc's RMF platform, for example, uses various in-house developed risk evaluation and control models/algorithms that are based on big data intelligence. While FintechInc used GBDT in its platform models, Fintech companies have used other machine learning algorithms including deep neural networks and k-nearest neighbors (Parrish and Fishman, 2018). There is no one approach and algorithm that fits all and oftentimes balance or trade-off is made to choose the right algorithm (Harlalka, 2018). Even with an appropriate algorithm, differences in the quantity and quality of training data and model parameters and variables would result in models with different levels of accuracy, discrimination (or bias), stability and timeliness, influencing the outcomes of risk evaluation.

Overall, unlike traditional technologies (for risk management), RMF platforms are able to access data sources and information that are not available to or not used by traditional lenders in their credit measures and decision-making process. Such alternative information includes a large variety of structured and unstructured data. RMF platforms can acquire access to this alternative information through either internally developed data aggregators or partnering with external data vendors. Although the various forms of partnership/business models and applications of artificial intelligence (e.g. machine learning) enable the use of new types of alternative information for better financial and other sensitive decisions, it also raises significant concerns not only for costs but also for privacy, security and discrimination (see Miller *et al.*, 2018; Parrish and Fishman, 2018). Therefore, I suggest that an important topic for future research is to examine a parsimonious set of alternative information types that can help Fintech lenders to simultaneously evaluate credit risk and thereby provide convenient online services while also minimizing the cost and compliance concerns.

5.3 Financial inclusion

Finally, I suggest that the use of alternative information in RMF platforms would not only impact loan outcomes but also consequently improve financial inclusion by eliminating constraints for inclusive finance such as *distance*. Financial inclusion (or inclusive finance) refers to efforts to make financial products and services available and affordable to all individuals and businesses (Grant and Kagan, 2019; Sapre, 2023). Distance to financial services has long been a constraint for inclusive finance in many developing countries (e.g. Akudugu, 2013; Demirguc-Kunt and Klapper, 2012). Individuals and businesses in remote and economically backward areas (with few local financial institutions) are often less likely to obtain credit because geographical distance affects lending decisions (Agarwal and Hauswald, 2010; Degryse and Ongena, 2005; Petersen and Rajan, 2002).

My study indicates that distance may become less predictive of loan outcomes when alternative information is used. Moreover, I suggest that risk ratings generated by the RMF platform could have a tighter relationship with the loan terms (loan price and availability) than those created by the loan officers. These indicate that if RMF platforms are superior to traditional technology (or loan officers) in risk profiling and thereby in identifying the "invisible" prime borrowers, these borrowers will receive better loan terms. In other words, RMF platforms and the use of various alternative information could potentially improve financial inclusion by allowing those borrowers at a distance to receive better credit ratings and lower-priced credit. Future research might further examine the impact of using alternative information on removing constraints (e.g. lack of credit history) on entry into the formal financial sector for rural SMEs and individuals.

6. Implications and conclusion

SMEs' access to bank credit has been an important topic in the literature. Although studies have shown that information asymmetries increase information risk and thereby influence SME lending decisions, scholars believe that the rapid emergence of Fintech would mitigate the information frictions in SME lending by expanding the information used in risk management. This study takes the first step in this direction by investigating how the use of alternative information in RMF platforms affects SME lending outcomes. Accordingly, my study and findings hold several implications for the research and practice of RMF platforms.

First, this study helps advance understanding of the specific impact of RMF platforms on SME lending outcomes. It shows how RMF platforms can leverage alternative data sources, such as online transaction history, social media activity and/or nontraditional credit scores, to assess the creditworthiness of borrowers. By incorporating these alternative data points, RMF platforms can provide a more comprehensive view of borrowers' financial profiles, enabling more accurate risk assessment and lending decisions. In other words, the present study helps researchers and practitioners gain a deeper understanding of one mechanism, i.e. alternative information utilization (Jagtiani and Lemieux, 2019), through which RMF platforms would influence the lending landscape [2].

Second, this study helps identify key success factors for RMF platforms in the context of SME lending and sheds light on how the factors contribute to the effectiveness and efficiency of RMF platforms. My findings indicate that these factors may include data quality and availability, advanced analytics and machine learning capabilities and partnerships and ecosystem integration. For example, by using advanced technologies, such as artificial intelligence and machine learning algorithms, to automate and streamline the lending process, RMF platforms can expedite the lending process and provide faster access to funds for borrowers. Also, collaborations and partnerships with other Fintech firms, financial institutions and data providers can enhance the effectiveness of RMF platforms. My study supports the view that there would be strong complementarities between Fintech companies and banks (Navaretti *et al.*, 2017). By partnering with small and community banks, for example, Fintech companies can focus on developing innovative business models and platforms while having banks originate the loans. Doing so would help Fintech companies and platforms become more profitable, less tangible and immune from the regulations to be applied to institutions that are making loans (Jagtiani and Lemieux, 2016).

Third, this study helps uncover challenges and limitations associated with using alternative information and RMF platforms. My findings highlight some potential pitfalls and ethical concerns that may arise when incorporating alternative data sources into lending practices. For example, although the use of alternative information would help eliminate constraints for inclusive finance, the reliance on alternative data sources and digital platforms may also exacerbate the digital divide and exclude certain individuals or communities without access to digital technologies and/or reliable internet connectivity (Alkureishi *et al.*, 2021). Also, complex algorithms and machine learning models can make the decision-making process less transparent and difficult for borrowers to understand. And lack of transparency can undermine trust and raise concerns about the fairness and accountability of lending practices (Lepri *et al.*, 2018). Ongoing industry collaboration, regulatory oversight and consumer advocacy are therefore needed to mitigate these pitfalls and concerns and promote fair and ethical lending practices in the Fintech space (Anagnostopoulos, 2018).

Fourth, this study helps stimulate further research in the field of RMF platforms by raising new questions and areas of investigation. These ideas and opportunities for future studies, as discussed earlier, would inspire researchers to delve deeper into specific aspects of alternative information usage, risk management techniques and regulatory implications. The corresponding results and findings would help offer guidance on the types of alternative information that are most valuable in assessing borrower creditworthiness, inform the development of algorithms and models used in risk assessment and enhance the performance and effectiveness of RMF platforms in supporting lending activities.

To conclude, this study provides valuable insights into how the use of alternative information in RMF platforms impacts SME lending. Although Fintech companies and platforms bring competition to the financial sector, my findings indicate that such competition would also lead to partnerships that can enhance efficiency and strengthen resilient incumbents. It is my hope that scholars will look beyond their own disciplines and use interdisciplinary ideas, theories and methods to study the issues brought by various Fintech innovations.

Notes

1. As a large amount and variety of alternative information has been used by Fintech companies in China, there is increasing interest in developing a Unified Fintech Regulatory System (an initiative by National Internet Finance Association of China) for data and information privacy.
2. Although the primary focus of this study is on the use of alternative information in SME lending, my literature review indicates that my insights should apply to individual lending as well. The difference lies primarily in the specific types of alternative information used to assess risk and make decisions.
3. WeChat is a Chinese multi-purpose messaging and social media application developed by Tencent for both personal and business uses.

References

Agarwal, S. and Hauswald, R. (2010), "Distance and private information in lending", *Review of Financial Studies*, Vol. 23 No. 7, pp. 2757-2788.

Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., Piskorski, T. and Seru, A. (2017), "Policy intervention in debt renegotiation: evidence from the home affordable modification program", *Journal of Political Economy*, Vol. 125 No. 3, pp. 654-712.

Akudugu, M.A. (2013), "The determinants of financial inclusion in Western Africa: insights from Ghana", *Research Journal of Finance and Accounting*, Vol. 4 No. 8, pp. 1-9.

Alessandrini, P., Presbitero, A.F. and Zazzaro, A. (2009), "Banks, distances and firms' financing constraints", *Review of Finance*, Vol. 13 No. 2, pp. 261-307.

Alkureishi, M.A., Choo, Z.Y., Rahman, A., Ho, K., Benning-Shorb, J., Lenti, G., . . . and Lee, W.W. (2021), "Digitally disconnected: qualitative study of patient perspectives on the digital divide and potential solutions", *JMIR Human Factors*, Vol. 8 No. 4, p. e33364.

Allen, F., Goldstein, I. and Jagtiani, J. (2018), "The interplay among financial regulations, resilience, and growth", *Journal of Financial Services Research*, Vol. 53 Nos 2/3, pp. 141-162.

Alyakoob, M. (2020), *Where You Live Matters: The Impact of Local Financial Market Competition on Banks' Response to Peer-to-Peer Lending*, SSRN.

Anagnostopoulos, I. (2018), "Fintech and Regtech: impact on regulators and banks", *Journal of Economics and Business*, Vol. 100, pp. 7-25.

Berger, A.N. and Udell, G.F. (1995), "Relationship lending and lines of credit in small firm finance", *Journal of Business*, Vol. 68 No. 3, pp. 351-381.

Berger, A.N. and Udell, G.F. (2006), "A more complete conceptual framework for SME finance", *Journal of Banking and Finance*, Vol. 30 No. 11, pp. 2945-2966.

Bertsch, C., Hull, I. and Zhang, X. (2016), "Monetary normalizations and consumer credit: evidence from fed liftoff and online lending", *International Journal of Central Banking, Forthcoming*.

Carbó-Valverde, S., Rodríguez-Fernández, F. and Udell, G.F. (2009), "Bank market power and SME financing constraints", *Review of Finance*, Vol. 13 No. 2, pp. 309-340.

Cassar, G., Ittner, C.D. and Cavalluzzo, K.S. (2015), "Alternative information sources and information asymmetry reduction: evidence from small business debt", *Journal of Accounting and Economics*, Vol. 59 Nos 2/3, pp. 242-263.

Chen, L. (2016), "From Fintech to Finlife: the case of fintech development in China", *China Economic Journal*, Vol. 9 No. 3, pp. 225-239.

Degryse, H. and Ongena, S. (2005), "Distance, lending relationships, and competition", *The Journal of Finance*, Vol. 60 No. 1, pp. 231-266.

Degryse, H., Matthews, K. and Zhao, T. (2018), "SMEs and access to bank credit: evidence on the regional propagation of the financial crisis in the UK", *Journal of Financial Stability*, Vol. 38 No. 3, pp. 53-70.

Demirguc-Kunt, A. and Klapper, L. (2012), "Measuring financial inclusion: the global Findex database", *The World Bank, Policy Research Working Paper*, Vol. 6025.

Dhar, V. and Stein, R.M. (2017), "FinTech platforms and strategy", *Communications of the ACM*, Vol. 60 No. 10, pp. 32-35.

Di Maggio, M. and Yao, V. (2021), "Fintech borrowers: lax screening or cream-skimming?", *The Review of Financial Studies*, Vol. 34 No. 10, pp. 4565-4618.

Diamond, D., Hu, Y. and Rajan, R.G. (2018), "Pledgeability, industry liquidity, and financing cycles", Working Paper, University of Chicago.

Duarte, J., Siegel, S. and Young, L. (2012), "Trust and credit: the role of appearance in peer-to-peer lending", *Review of Financial Studies*, Vol. 25 No. 8, pp. 2455-2484.

Frame, S., Srinivasan, A. and Woosley, L. (2001), "The effect of credit scoring on small-business lending", *Journal of Money, Credit and Banking*, Vol. 33 No. 3, pp. 813-825.

Ge, R., Feng, J., Gu, B. and Zhang, P. (2017), "Predicting and deterring default with social media information in peer-to-peer lending", *Journal of Management Information Systems*, Vol. 34 No. 2, pp. 401-424.

Giannetti, M., Liberti, J. and Sturgess, J. (2017), "Information sharing and rating manipulation", *The Review of Financial Studies*, Vol. 30 No. 9, pp. 3269-3304.

Godbillon-Camus, B. and Godlewski, C.J. (2005), "Credit risk management in banks: hard information, soft information and manipulation", available at: https://ssrn.com/abstract=882027 (accessed 6 January 2022).

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W. (2018), "On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services", *Journal of Management Information Systems*, Vol. 35 No. 1, pp. 220-265.

Grant, M. and Kagan, J. (2019), "Financial inclusion", available at: www.investopedia.com/terms/f/financial-inclusion.asp (accessed 6 January 2022).

Harlalka, R. (2018), "Choosing the right machine learning algorithm", Hackernoon, available at: https://hackernoon.com/choosing-the-right-machine-learning-algorithm-68126944ce1f (accessed 6 January 2022).

Härle, P., Havas, A., Kremer, A., Rona, D. and Samandari, H. (2015), *The Future of Bank Risk Management*, McKinsey Working Papers on Risk.

Herzenstein, M., Sonenshein, S. and Dholakia, U. (2011), "Tell me a good story and I may lend you my money: the role of narratives in peer-to-peer lending decisions", *Journal of Marketing Research*, Vol. 48 No. SPL, pp. 138-149.

Hoberg, G. and Phillips, G. (2016), "Text-Based network industries and endogenous product differentiation", *Journal of Political Economy*, Vol. 124 No. 5, pp. 1423-1465.

Jaffee, D.M. and Russell, T. (1976), "Imperfect information, uncertainty, and credit rationing", *The Quarterly Journal of Economics*, Vol. 90 No. 4, pp. 651-666.

Jagtiani, J. and Lemieux, C. (2016), "Small business lending after the financial crisis: a new competitive landscape for community banks", *Economic Perspectives*, Vol. 3, pp. 1-30.

Jagtiani, J. and Lemieux, C. (2019), "The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform", *Financial Management*, Vol. 48 No. 4, pp. 1009-1029.

Jung, D., Dorner, V., Glaser, F. and Morana, S. (2018), "Robo-advisory: digitalization and automation of financial advisory", *Business and Information Systems Engineering*, Vol. 60 No. 1, pp. 81-86.

Lepri, B., Oliver, N., Letouzé, E., Pentland, A. and Vinck, P. (2018), "Fair, transparent, and accountable algorithmic decision-making processes: the premise, the proposed solutions, and the open challenges", *Philosophy and Technology*, Vol. 31 No. 4, pp. 611-627.

Liberti, J.M. and Petersen, M.A. (2019), "Information: hard and soft", *The Review of Corporate Finance Studies*, Vol. 8 No. 1, pp. 1-41.

Lin, M., Prabhala, N. and Viswanathan, S. (2013), "Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending", *Management Science*, Vol. 59 No. 1, pp. 17-35.

Lu, Y., Gu, B., Ye, Q. and Sheng, Z. (2012), "Social influence and defaults in peer-to-peer lending networks", International Conference on Information Systems, ICIS, pp. 1797-1813.

Miller, M., Medine, D. and Montes, F. (2018), "Data protection and privacy for alternative data", *GPFI-FCPL Sub-Group Discussion Paper*, World Bank Group.

Mishkin, F.S. and Strahan, P.E. (1999), "What will technology do to financial structure?", NBER Working Paper No. 6892.

Navaretti, G.B., Calzolari, G. and Pozzolo, A.F. (2017), "FinTech and banks: friends or foes?", European Economy Banks, Regulation, and the Real Sector.

Ngai, J.L., Qu, J. and Zhou, N. (2016), "What's next for China's booming fintech sector?", Financial Services, McKinsey&Company.

Owens, J. and Wilhelm, L. (2017), *Alternative Data Transforming SME Finance*, International Finance Corporation, Washington, DC.

Parrish, L. and Fishman, J. (2018), "Alternative data across the loan life cycle: how FinTech and other lenders use it and why", *Experian*.

Petersen, M. and Rajan, R.G. (1994), "The benefits of lending relationships", *The Journal of Finance*, Vol. 49 No. 1, pp. 3-37.

Petersen, M. and Rajan, R.G. (2002), "Does distance still matter? The information revolution in small business lending", *The Journal of Finance*, Vol. 57 No. 6, pp. 2533-2570.

Philippon, T. (2016), "The fintech opportunity", National Bureau of Economic Research, No. w22476.

Puschmann, T. (2017), "Fintech", *Business and Information Systems Engineering*, Vol. 59 No. 1, pp. 69-76.

Ramcharan, R. and Crowe, C. (2013), "The impact of house prices on consumer credit: evidence from an internet bank", *Journal of Money, Credit and Banking*, Vol. 45 No. 6, pp. 1085-1115.

Riggins, F.J. and Weber, D.M. (2017), "Information asymmetries and identification bias in P2P social microlending", *Information Technology for Development*, Vol. 23 No. 1, pp. 107-126.

Rudegeair, P., Glazer, E. and Simon, R. (2015), "Inside J.P. Morgan's deal with on deck capital", available at: www.wsj.com/articles/inside-j-p-morgans-deal-with-on-deck-capital-1451519092 (accessed 6 January 2022).

Saha, P., Bose, I. and Mahanti, A. (2016), "A knowledge based scheme for risk assessment in loan processing by banks", *Decision Support Systems*, Vol. 84 No. 1, pp. 78-88.

Saifurrahman, A. and Kassim, S.H. (2023), "Mitigating asymmetric information to enhance MSME Islamic financial inclusion by Islamic banks in Indonesia", *Qualitative Research in Financial Markets*, Vol. 15 No. 3, pp. 453-470.

Sapre, N. (2023), "Financial inclusion: philosophical and methodological underpinnings", *Qualitative Research in Financial Markets*, Vol. 15 No. 3, pp. 445-452.

Urquhart, C. (2012), *Grounded Theory for Qualitative Research: A Practical Guide*, Sage, Thousand Oaks, CA.

Xu, J.J. and Chau, M. (2018), "Cheap talk: the impact of lender-borrower communication on P2P lending outcomes", *Journal of Management Information Systems*, Vol. 35 No. 1, pp. 53-85.

Corresponding author
Jie Yan can be contacted at: jyan@utep.edu

Appendix 1. Interview guide for December 2020 and January 2021 interviews

Date:	Name:
Job Title:	
Questions	
Please describe your job title and responsibilities.	
Could you briefly describe the development of the partnership between FintechInc and LoanBank?	
Do you know the criteria and process LoanBank's loan officers used to assess SME credit ratings before the partnership with FintechInc, particularly focusing on the information sources and evaluation methods used? If so, could you help describe them?	
Could you briefly describe how FintechInc customized its RMF platform for LoanBank?	
Could you explain the key modules (ERM and OMM) within FintechInc's RMF platform, their functions, and how they contribute to LoanBank's improved efficiency and reduced lending costs?	
What specific data sources and types are retrieved by the ERM and OMM modules, and how do they differ in their approach to evaluating credit quality and monitoring business operating conditions for SMEs?	
How do ERM and OMM generate standardized risk ratings for SMEs, and how is this information utilized by LoanBank's loan officers and branch presidents in loan approval and terms determination?	
How does the partnership between LoanBank and FintechInc change the roles and responsibilities of LoanBank's loan officers in the lending process, particularly in terms of investigation, verification, and monitoring?	
Follow-up Question	
Can you elaborate on how the ERM model links personal credit to the enterprise and how changes in these variables affect the risk assessment using the GBDT algorithm?	

Source: Created by the author

Appendix 2. CPR template with alternative information

Business Name

Corporate Panorama Report

*Report generation time

*The content of this report is an overview of the business's risk profile as of the generation time

*The content of this report is all based on the results obtained from the integration and calculation of FintechInc's data and information, and only provides a reference for your decisions

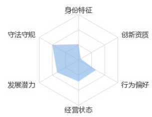
Business description

Logo	
Website	
About	

Business risk assessment

Enterprise Risk

2: Average



Operation Risk

3: Above Average

Business registration information

Name	
Legal representative	
English Name	
Registration status	
Unified social credit code	
Organization Code	
Registered capital	
Date of establishment	
Approval date	
Industry	
Type of enterprise	
Registered location	
Registration authority	
Contact	
Business Scope	

(*continued*)

Founder/owner

Location

Actual address		Province	
Coordinate address		City	
Standard address		District	
Address level		Township	
Street direction		Street	
Street distance		Shopping district	

Shareholders and funding information

Name	Type	Amount	Ratio	Date

Historical exit shareholder

Name	Entry date	Exit date	Duration

Key management personnel

Board member
Board of supervisors
Upper manager

Business change information

Change item	Pre-change	Post-change	Change date

Chattel mortgage information

Liquidation information

Legal assistance history

Administrative penalties history

Abnormal operations

Serious violations of law

Corporate foreign investments

Company name	Amount	Ratio	Date

Branch office

Name	Province	Registration status	Date of establishment

External investments of legal representatives

Company name	Amount	Ratio	Date

(*continued*)

- External appointments of legal representatives

Company name	Position	Company's legal representative	Registration status	Date

- External investments of upper managers

Manager name	Company name	Amount	Ratio	Date

- External appointments of upper managers

Manager name	Company name	Position	Company's legal representative	Registration status	Date

- Projects
- Honor
- Patent
- Trademark
- Copyright
- Trade product information
- U.S. trading partner
- Customs credit rating
- Customs administrative penalty information
- Court Referee
- Credit China Trustworthy Red list
- Credit China Trustworthy Blacklist
- News lyrics

Source: FintechInc CPR Template