Small Bus Econ (2024) 63:1225–1247
https://doi.org/10.1007/s11187-023-00857-0

RESEARCH ARTICLE

Who is lending to small and micro family business in China: evidence from CHFS data

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Accepted: 8 December 2023 / Published online: 27 December 2023

Abstract This article examines the impacts of traditional and digital finance on the financing of small and micro family businesses (SMFBs) in China. Based on a comprehensive sample of 8625 SMFBs from China Household Financial Survey (CHFS) data, our results from Tobit regressions showed that traditional finance did not reduce the financing constraints of SMFBs, while digital finance significantly promoted SMFBs' access to credit. Further analyses revealed that additional credit from digital finance helped SMFBs increase their business scale and operational capability, but decreased their profitability due to the high loan cost associated with digital finance. Our findings imply on the one hand that government policies aiming at encouraging commercial banks to provide loans to small and micro enterprises in China have been producing very limited effects. On the other hand, digital finance is an effective micro-loan provider for SMFBs thanks to its strong ability in collecting and integrating individuals' credit history data, although more measures are needed to take for turning this financing enhancement of SMFBs into their profit growth. These findings enrich the literature on family business by comparing the effectiveness of different financing sources for SMFBs in China. It provides important insights for future policy design on how to ease financial constraints in SMFBs and support the development of SMFBs.

Plain English Summary This study investigated the effects of traditional finance and digital finance on the financing of SMFBs in China. Tobit regression results indicated that traditional finance did not alleviate the financing constraints experienced by SMFBs. Despite the use of advanced financial technologies and the encouragement from government policies, commercial banks are still unwilling to extend credit to SMFBs. Digital credit, by contrast, enhanced the financial accessibility for SMFBs. Moreover, increased financing from digital finance was positively associated with SMFBs' business expansion and operational ability, although it did not enhance the profitability of SMFBs in a short run. To effectively promote the financing and business success for SMFBs, efforts from multiple agents need to be taken. The owners of SMFBS should involve more in-depth in business operation and take greater responsibility for enterprise management. Policymakers should consider commercial banks' objectives and interests, when encouraging them to lend to small and micro businesses, and monitor the true interest rate of digital financial services.

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Keywords Traditional finance · Digital finance · SMFBs · Financing constraints

JEL Classification G21 · G30 · G50

1 Introduction

Family businesses are effective creators of civic wealth that play a critical role in economic development (Lumpkin & Bacq, 2022). In China, family and small businesses are highly overlapped. Small and micro firms account for over 90% of total companies and 80% of employment,[1] and over 85% of private enterprises are family businesses.[2] Small and micro family businesses (SMFBs) are a major component of Chinese economy. However, the credit support and financial resources available to them in China do not catch their significant contributions to the national economy, which has become one of the major obstacles that hinders the development of SMFBs. However, past research on family businesses mainly focuses on the internal governance and management of large family-owned corporations (Chiang et al., 2022; Kandade et al., 2021; Singh et al., 2021; Tiberius et al., 2021; Waterwall & Alipour, 2021). At the same time, most studies of small businesses neglect the micro-sized firms, which are the majority of them, due to data availability. The primary goal of this research is to fill these gaps by investigating the impacts of traditional and digital finance on the financial accessibility of SMFBs.

The financial market in China primarily consists of traditional and digital finance, referring to financial services provided by traditional commercial banks and digital financial enterprises developed by Internet companies, respectively (Guo & Wang, 2020). They are the major micro-lending providers (Guo & Wang, 2020). Small and micro enterprises (SMEs) are often discriminated in traditional lending market and facing more financing constraints comparing to their large counterparts, due to their small size, imperfect governance, insufficient information disclosure, and limited financial abilities (Deng & Zhao, 2017). SMFBs, which share the typical problems inherent in SMEs, have the same difficulties in obtaining credit from traditional finance. Lending to SMFBs that do not have documentary credit history always involves information asymmetry and high risk. In China, heavy reliance of banks on the national credit rating system, which is generated with very limited credit card and personal loan data, for borrowers' information makes them unable to effectively deal with the risks originated from information insufficiency. Even Chinese banks are undergoing a digital transformation; the credit rating is still the primary source of information for banks. Therefore, the information asymmetry persists, and banks are reluctant to provide loans to SMFBs.

Microfinance may promote the availability of credit for SMFBs in that it aims at providing small loans to disadvantaged social groups who are excluded from formal financial sectors (Jaffer, 1999). It is acknowledged that microfinance can help the poor alleviate their poverty and improve their socioeconomic conditions (Banerjee et al., 2015). However, to effectively and sustainably provide loans to the poor, micro financial institutions have to achieve financial sustainability themselves. Under the pressure for financial sustainability, some microfinance organizations start engaging in "credit rationing" practices, through which they concentrate their loans to wealthier clients and exclude poorer population from their services. Such practices lead to "mission drift" that reduces the breadth and depth of social outreach. The problems of "credit rationing" and "mission drift" become more serious microfinance institutions are transforming from an NGO to a bank-like organization (Baker, 2021; Armendáriz & Szafarz, 2011; Chahine & Tannir, 2010; D'Espallier et al., 2017; Shaw et al., 2019). With a smaller economic scale and lower social status, SMFBs are even more likely than a typical SMEs to be the victims of such activities by microfinance organizations. These issues tend to be much more severe in China for two reasons. First, unlike many other countries, China lacks traditional NGO-based microfinance institutions. Second, there are some for-profit microfinance companies, but they are generally tiny in size, have limited funding resources, lack of financial professionals, and are ill-equipped with digital technologies. Among these disadvantages, the low level of digitalization is particularly crucial, as for microfinance organizations to achieve social mission

[1] http://www.gov.cn/xinwen/2019-06/25/5402948/files/f59aaafc00da4c848a322ac89fdec1e5.pdf

[2] https://www.pbcsf.tsinghua.edu.cn/info/1184/2263.htm PwC's "2021 Global Family Business Survey - China Report"

and financial sustainability, some measures such as a "solidarity lending" system (Jaffer, 1999) and digitally enhanced financial inclusion techniques (Baker, 2021) have to be developed to deal with information asymmetry problem in their loan-providing services. Consequently, "credit rationing" and "mission drift" are prevalent in these microfinance companies. For example, most of these companies concentrate their loans with one single client.[3] Microfinance organizations at its current stage are not a major micro-lending provider and their contribution to SMFBs' financing is minimal.

The emergence and development of digital finance[4] can potentially change the financing situation for SMFBs. Compared to traditional banks, digital finance can overcome the geographic barrier in financial services, simplify loan approval procedure, and greatly improve the efficiency of lending services (Guo & Wang, 2020; Huang & Huang, 2018; Nie et al., 2021). With the use of advanced technologies, digital financial institutions are better equipped to collect and process information, which enables them to alleviate information asymmetry problems and reduce credit risks faced by traditional banks. Therefore, digital financial institutions are more willing and able to issue loans to households and SMEs (Gomber et al., 2018; Sheng & Fan, 2020; Wang, 2015). Moreover, Chinese people have intensively adopted digital technologies in their financial and other daily activities (e.g., digital payment: in 2020, the total size of third-party Internet payments in China reached 271 trillion yuan), and most of these activities take place on the platforms of Internet companies. By integrating the information generated by these digitalized behaviors, digital financial institutions can obtain comprehensive credit history of potential borrowers. These advantages make digital finance the most effective micro-lending provider for SMFBs.

This research investigates the roles that traditional bank lending and digital finance play on SMFBs' financing in China. Our empirical results using the data from China Household Financial Survey Project (CHFS) show that traditional finance does not ease the financing constraints of SMFBs, while digital finance improves SMFBs' access to credit. Further research reveals that accessing more credit helps SMFBs to expand their business and improve operating ability, but hurt their profitability. Our study contributes to the literature in several aspects: (1) Enrich the literature on family business by looking into the financing aspects of small and micro family businesses. (2) Extends the research on small businesses. Previous studies of SMEs generally use a small sample and focus on the business characteristics of those companies. By using the family level data of CHFS 2015, 2017, 2019, we incorporate a large sample of small businesses, especially the micro-sized firms into our study, and consider the characteristics in both business operation and household aspects. (3) Simultaneously examines the impacts of traditional and digital finance on the financing of SMFBs, and provide a comprehensive and in-depth study on the current state of SMFBs' financing through a series of heterogeneity analyses. (4) Conducts extended analyses that generate further insights on how increased credit for SMFBs affects their business performance.

Even though this research is based on small and micro family business firms in China, our findings may be applicable to small businesses in many other countries. According to Gong and Zhong (2005), many businesses around the world, including small businesses, are family owned. For example, they observe that family business accounts for about 80% ~ 90% of the total number of enterprises in North America; in the USA, 80% of the SMEs are family-owned; in terms of the share of family businesses in national GDP, the USA is 50%, South Korea is 48.2%, and Malaysia is 67.2%. The rest of the paper is organized as follows: Section 2 introduces the research background, literature, and contributions. Section 3 describes the data, variables, and models. Section 4 presents the empirical results and robustness tests. Section 5 summarizes the full text and makes our recommendations.

2 Literature

It has been a long-existing problem for SMFBs to obtain credit in traditional lending market. Like a typical small business, SMFBs often encounter more and severer financial constraints and exclusion

[3] http://www.21jingji.com/article/20220309/herald/607e81d3df4b1c43b8f9f5a57fc35a41.html

[4] According to Peking University Digital Financial Inclusion Index of China (PKU_DFIIC), a widely used measure of digital finance the digital financial business index has grown from 101.60 in 2011 to 424.23 in 2021.

because of their imperfect corporate governance structure, non-standard financial management, insufficient information disclosure, limited collaterals and mortgage capacity, and difficulty in finding a third-party as a financing guarantee (Deng & Zhao, 2017). These inherent disadvantages in SMEs lead to information asymmetry and transaction cost problems in the lending market that prevent traditional banks from extending credit to small businesses (Tucker & Lean, 2003). Because SMEs usually are not publicly traded securities, they are not legally or institutionally bound to disclose verifiable information. As a result, public information on small businesses available to traditional banks are very limited. Even if it is provided, the authenticity and quality of those information may still be deemed questionable. Such problem of information asymmetry makes traditional banks face higher risks of adverse selection and moral hazard (Craig et al., 2007; Stiglitz & Weiss, 1981). Furthermore, for traditional banks, the cost of collecting and verifying soft information is high (Ang, 1991), and they need to pay fixed and variable costs for each lending. Small and micro enterprise loans, which are characterized by small amount, short term, and high frequency, increase the transaction and risk management costs for banks (Bratton, 1986; Bester & Hellwig, 1987; Bester, 1987; Binks & Ennew, 1996; Hammond & Prahalad, 2004; Deng & Zhao, 2017; Tyler & Zhao, 2018). Their profit margin of financial services to small businesses is threaten, and traditional banks are reluctant to lend to SMEs.

The information asymmetry and translation cost problems are potentially more striking in traditional lending market of China due to two institutional characteristics. First, Chinese banks heavily rely on the national credit rating system to collect information of potential borrowers, Yet, that system itself is in a very early stage of development. A lack of credit card and personal loan traditions in China makes the data sources available for the rating very limited, and it conveys little information on borrowers' personal credit history for banks. Second, in 2004, China stared marketizing bank lending rates and expanding the room for lending rate fluctuation. However, at the operational level, lending rates are still affected by national macroeconomic policies and subject to the window guidance of regulators (Shen et al., 2018; Yu et al., 2015). As a result, the under-marketization of lending rates has led to de facto restrictions and interventions on bank lending rates in the process of interest rate marketization (Chu & Hu, 2020). Combined with the high cost and risky nature of the microfinance business, banks which are risk averse in China, have opted for "credit rationing" as a solution. Although small and local banks are better at collecting soft information and more willing to build good relationships with small businesses (Berger & Udell, 2002; Stein, 2002), some scholars have found that the roles of small and local banks in improving the financing situation of SMEs may not be as significant as believed. For example, based on a proprietary loan-level dataset from Mexico, Canales & Nanda (2012) argue that decentralized banks are more responsive to their own competitive environment, and cherry pick customers and restrict credit when they gain market power. In the studies of SMEs in Argentina, Chile, Colombia, Mexico, Peru, Puerto Rico, and Venezuela during 2002–2006, de la Torre et al. (2010) contend that the intensification of bank involvement with SMEs is neither led by small or niche banks nor highly dependent on relationship lending. Jayaratne & Wolken (1999) use the data on small business borrowers from the 1993 National Survey of Small Business Finance in the USA and find that the probability of a small firm having a line of credit from a bank does not decrease in the long run when there are fewer small banks in the area. In China, the financial system has not yet fully achieved "multi-level, wide coverage, and differentiation." [5] The underdevelopment of small and local banks further restricts the help SMEs can obtain from traditional lending market. Consequently, small businesses always rely on private sources for their financing needs. Only if the financial resources from insiders are exhausted, they will resort to external debt provided by commercial banks and other financial institutions (Berger & Udell, 2002).

In the past years, banks in China have been pursuing digital transformation and have started providing financial services through their online platforms (Xie & Wang, 2022). While using financial technologies may help traditional banks to solve the

[5] The information comes from the "2019–2020 Small and Micro Financing Status Report" jointly published by the All-China Federation of Industry and Commerce, the National Finance and Development Laboratory, and the Ant Group Research Institute.

information asymmetry and transaction cost issues in small business lending to some extent, the enormous investments and costs associated with digital transformation, such as investment in technological infrastructure (Cappa et al., 2021), R&D costs, and insurances to protect against privacy breaches (Chesbrough et al., 2018), prevent them from fully adopting those technologies. More importantly, to what extent that the digital advancement of banks can reduce information deficiency depends how lenders, intermediaries, and borrowers exchange their information under certain institutional context. As mentioned above, Chinese banks rely heavily on the national credit rating system for the information of potential borrowers, which in turn, is based on very limited historical credit card and personal loan data. In addition, while people in China have widely used digital technologies in many aspects of their life, these activities are largely conducted through the platforms of Internet companies, and the information generated is not integrated into the bank and national credit system. As a result, simple proceeding in digital transformation by banks does not greatly enhance their capability of information collecting and processing.

Microfinance may promote access to financing for SMFBs. With a social mission of helping the poor, microfinance aims at providing financial services to disadvantaged social groups such as individuals and households with low income or lack of assets as well as small business owners, who are usually concentrated in rural areas and the informal sector, and they are excluded from formal financial institutions (Kabeer, 2001; Khandker, 2005; Mair et al., 2012). Most microfinance institutions nowadays are still operated by NGOs. These institutions receive donor grants and provide small short-term loans to borrowers without conventional collateral, but typically require the loan proceeds to be used for investment in productive capital. It has been recognized that microfinance can help the poor alleviate their poverty and improve their socioeconomic conditions by extending credit to them, although the positive impact may not be as significant as previously anticipated (Banerjee et al., 2015).

One important premise for microfinance institutions to effectively and sustainably provide loans to the poor is that they can maintain financial sustainability themselves. However, financially self-sustaining is not an easy goal for many microfinance institutions. Firstly, the dependency on donors and limited access to commercial funding restricts their financial resources, and the lack of financial professionals and good governance structure hurts their management and performance (Frank, 2008; Mersland, 2009). More importantly, micro-lending to the poor is also involved with serious information asymmetry problem. For microfinance institutions, collecting and verifying soft information, screening and monitoring borrowers, and enforcing credit agreements are costly where documented credit histories do not exist for the borrowers and the businesses are very small (Jaffer, 1999). As a result, microfinance is associated with high risk and cost. In order to improve financial performance, "credit rationing" practices emerge in microfinance institutions, through which they concentrate their loan provisions to wealthier clients and exclude lots of potential borrowers, especially the poorer ones, from their financial services (Jaffer, 1999; Armendáriz & Szafarz, 2011, Chahine & Tannir, 2010). In addition, because larger loans are more profitable (Mersland & Strøm, 2010), microfinance institutions may also increase the size of their loans to wealthy clients and decrease the loan size for the poorer ones. Such practices reduce the breadth and depth of social outreach of microfinance institutions and lead to "mission drift," where microfinance institutions are deviated from their social mission of helping the poor (Armendáriz & Szafarz, 2011, Chahine & Tannir, 2010). In terms of small businesses, because SMFBs have a smaller size and lower social status, they are more likely than a typical SMEs to be the victims of "credit rationing" in microfinance.

The way microfinance institutions are developed in China indicates that their roles in improving SMFBs' financing are more limited. With a weak cultural tradition of donation, NGO-based microfinance is significantly underdeveloped in China. Although there are some for-profit microfinance companies, their contribution to the financing of SMFBs is limited for several reasons. Firstly, these companies are very small in size, and they have limited financial resources because they are not allowed to receive public deposits and can only rely on a few shareholders for funding. Secondly, the lack of financial professionals in their crew and typically a problematic corporate governance structure, most of these companies end up with bad performance and financial insufficiency. Thirdly, the digitalization level is very low within these companies. This disadvantage is crucial because for microfinance organizations to achieve their social mission and financial sustainability, some measures such as a "solidarity lending" system (Jaffer, 1999) and digitally enhanced financial inclusion techniques (Baker, 2021) have to be developed to deal with information asymmetry problem in their loan-providing services. As a result of these problems, microfinance companies in China engage in more serious "credit rationing" and "mission drift." For example, most of these companies concentrate their loans with only one client.[6] Therefore, microfinance at its current stage is not an effective micro-lending provider in China.

Internet enterprises have unique technological advantages and do not suffer the pain of digital transformation (Wang & Zhao, 2020). With their technologies in the Internet, big data, blockchain, and artificial intelligence, digital finance developed by Internet companies are more capable of providing financial services to SMFBs than traditional banks. Firstly, digital finance can overcome geographic barrier, by which it increases the access and availability of financial services for more people, especially those advantaged social groups. Secondly, it can simplify loan approval procedures and thus greatly improve the efficiency of lending services. Thirdly, digital finance decreases the threshold cost of financial services by introducing competition (Guo & Wang, 2020; Huang & Huang, 2018; Nie et al., 2021). Most importantly, with the full use of advanced technologies, digital financial institutions are better at collecting, processing, and transmitting soft information, which enables them to alleviate the persistent problems of information asymmetry and transaction cost associated with microfinance in traditional lending market (Gomber et al., 2018; Sheng & Fan, 2020; Wang, 2015). Moreover, by integrating the information generated by these digitalized behaviors, digital financial institutions can get a much more comprehensive credit history of potential borrowers.

Therefore, digitally enhanced financial services are more inclusive (Baker, 2021;Shaw et al., 2019; Gabor & Brooks, 2017; Langevin, 2019). In the study of digital finance, Wang (2015) believes that digital finance can change the position of the financial supply curve in traditional financial market, make up the supply gap to a certain extent, and reduce the degree of credit rationing. Tang et al. (2020) and Xie & Zhu (2021) confirm that digital finance effectively solves the problem of "difficult and expensive financing" for enterprises, and drives enterprises to leverage and stabilize financial conditions, improve profitability, and increase technological innovation output. Actually, providing financial services to SMEs can be an important stimulus for the advancement of digital finance. For example, Guo & Yin (2022) find that the scale of household credit motivates digital financial institutions to conduct innovation activities and increase investment in R&D for household industry and commerce. Most of these studies are based on listed companies, and only a few focus on small firms. Even if small businesses are under examination, the data being used is typically coming from special surveys and tend to have sample sizes. Our research extends this line of investigation by using a large sample of small businesses that includes micro business firms. Based on the above discussion, we derive the following hypothesis:

- **Hypothesis 1:** Digital finance mitigates financing constraints for SMFBs, while traditional finance does not.

Enterprise scale plays an important role in business operation and success. Companies with a large size tend to have higher profit rates (Hall & Weiss, 1967). The larger the enterprise, the more capable it can be to overcome the negative impacts of financial, legal, and corruption issues on its growth rate (Beck et al., 2005). After obtaining additional credit from digital finance, SMFBs tend to use it to expand their business scale. However, fintech companies generally charge higher loan interest rates than licensed financial institutions. For example, "Huabei" of Alipay is similar to the credit card business from commercial banks, but the installment handling fee is much higher than that of the latter.[7] Therefore, while extra credit from digital finance may help SMFBs increase their business size, the high costs associated with the loans may

[6] http://www.21jingji.com/article/20220309/herald/607e81d3df4b1c43b8f9f5a57fc35a41.html

[7] https://baijiahao.baidu.com/s?id=1682277932815075753&wfr=spider&for=pc

offset the benefits from business expansion. With both revenues and costs increasing, we cannot be very confident that the company's profits will also increase (Beck et al., 2005; Galindo & Schiantarelli, 2002). For SMFBs that use digital finance for extra credit, their profitability may not necessarily increase or even decrease, at least in a short run. Therefore, we propose hypothesis 2:

- **Hypothesis 2:** Obtaining credit can help SMFBs to increase their business scale, but not their profitability.

Incorporating micro-sized family businesses into the study will not only extend the literature on the financing of small businesses, but generates important practical implications under China's context. First of all, small businesses are the backbone of Chinese national economy, and among them, over 80% are micro-ones.[8] In order to get a full picture about small business financing and promote economic development, it is crucial to add micro business firms into the study sample. Secondly, compared to a typical small business, the micro-sized firms are smaller in scale and have more governance issues and lower social status; the financial exclusion experienced by them may be much severer and worthy of further examination. Lastly, past research on small business financing primarily investigates the company-side factors. When the owner of a business has great impacts on the operation, governance, and performance of the company, the characteristics of the owner are crucial for its financing. This is exactly the case of SMFBs where the owner or the family is the key player for the business, and information on the company-side is extremely limited or unreliable. So, when banks are deciding to issue loans to a SMFB, they will try to collect the soft or transparent information of the owner to make up the information deficiency on the business side (Berger et al., 2014). Hard information on the business owner such as personal credit history is also often used by the banks to infer future loan performance (Berger & Black, 2011; Kallberg & Udell, 2003). Therefore, investigating the characteristics of the owner is essential for the research on SMFBs' financing.

3 Data, variables, and model

3.1 Data source

Three sources of data are used in this study:

1) The data of SMFBs comes from the China Household Financial Survey Project (CHFS) organized and managed by China Household Financial Survey and Research Center, Southwestern University of Finance and Economics (Gan et al., 2014).[9] The CHFS dataset offers rich information on small and micro family businesses, including employment, assets and liabilities, income and consumption, social security and insurance, as well as information on the family and business characteristics, conducted biennially since 2011, covering 29 provinces, 170 cities, and 343 districts and counties across China, with a sample size of 34,643 households in 2019. The sample size in CHFS 2021 was reduced to 22,027 households due to the impact of COVID-19. To ensure data quality, we restrict our sample to 2015, 2017, and 2019 data, which is representative at national, provincial, and sub-provincial levels. Using family-level micro data from CHFS not only enables us to incorporate the vast majority of small business firms into the study, but allow us investigate the impacts of family-size on the financing of SMFBs.
2) The data of the city's economic indicators comes from Chinese Research Data Services Platform (CNRDS).[10] It is a high-quality and comprehensive data platform for Chinese economic, financial, and business research.
3) For digital finance, we use Peking University Digital Financial Inclusion Index of China (PKU_DFIIC) developed by the Finance Research Center of Peking University and Ant Group Research Institute. This index measures the development of digital

8 http://www.gov.cn/xinwen/2014-03/31/content_2650031.htm

9 The CHFS data used in this article relates to the home address of the respondent. In order to protect the privacy of the respondent, this data cannot be disclosed. Data not involving home address can be obtained from the website of the research center: https://chfs.swufe.edu.cn/sjzx/sjsq.htm

10 The datasets of city's economic indicators and digital finance are available from the corresponding author on reasonable request.

financial services carried out by Internet companies at various prefecture-level cities in China. It is considered as one of the most comprehensive indicators of digital finance in China and widely used by Chinese scholars. The index from PKU_DFIIC system consists of five dimensions;[11] we used the digital credit index for our search because it best reflects the development of loan business in China's digital finance.

3.2 Sample selection

We use the overlap of small and micro enterprises and family businesses as our final sample, which is chosen through the following three steps. Firstly, we identify the households that are currently running a business by the question from CHFS: "Is your family engaged in any production and operation of industrial or commercial businesses, including individual and household business, leasing, transportation, online stores, and enterprises?" 15,631 households out of a total of 111,924 answer "yes" to this question.

Next, we select out small and micro businesses from this subsample. Small businesses usually refer to small and medium-sized enterprises identified by their sizes. For example, some scholars consider "firms with up to 500 (full-time-equivalent) workers" as small businesses (Berger et al., 2014). Others tend to use the EU-level thresholds in terms of employment (250 workers), net sales (50 million euros), and total assets (43 million euros) (Ylhäinen, 2017). Banks generally identify small businesses based on their average annual sales. The thresholds being used vary by country, depending on the size of the economy and corporate structure characteristics (de la Torre et al., 2010). In 2021, the Chinese government issued the "Revised Draft for Comments on the Classification Standards for Small and Medium-sized Enterprises," which defines small businesses as encompassing medium-sized, small-sized, and micro-sized enterprises. The classification criteria are based on several factors, including the number of employees, operating income, total assets, and industry. We use this policy to choose our sample of small and micro enterprises, which consists of 15,247 households.

Finally, family businesses are identified from the small and micro business sample. Different methods have been used to classify family business provided what kind of data the researchers have. Anderson et al. (2003) use the ownership dummy, which measures the proportion of the family's ownership stake relative to other stakeholders and the fraction of family equity holdings in total outstanding shares as the primary indicator of a family business. Zellweger et al. (2012) consider three factors as the criteria for family businesses, including whether the firms have identified themselves as family enterprises, whether the families hold a controlling interest, and whether the firms employ at least two family members. Deephouse & Jaskiewicz (2013) identify family businesses by whether the family's name is included in the firm's name, the total amount of voting rights held by the family, and whether at least one family member is present on one of the company's boards. For our small and micro business sample, the CHFS data does not disclose the name of the companies, neither public "hard information" of these businesses is available within and outside of CHFS. Therefore, we can only define family businesses based on the questions available in CHFS. Specifically, we classify a business as a family business if the family accounts for more than 50% of the total asset investment in the business it participates in.[12] After excluding samples with the heads of households younger than 18 or older than 80, our final sample ends up with 14,597 households.[13]

3.3 Variables selection and setting

3.3.1 *Dependent variables*

The dependent variable for basic regression is the total amount of industrial and commercial liabilities for households (*liabilities_amo*). Instead of using the

[11] PKU_ DFIIC includes digital credit business index, digital payment business index, digital monetary fund business index, digital insurance business index, and digital investment business index; each reflects the development level of a specific aspect of digital finance business.

[12] We believe that if a family owns more than 50% of the total asset investment in the business it participates in, the family has absolute control over the business.

[13] After removing the missing values of all variables, the final valid samples for basic regression are 8625.

raw form of the amount liabilities, we add 1 to the amount of liabilities and take the logarithm.

3.3.2 Independent variables

The independent variables include traditional finance and digital finance. For traditional finance, we use the density of bank branches in the city where the family business is located (*bank_density*) to reflect the development of local credit market. It is calculated by dividing the total number of bank branches in the city by the average annual population of the city.

Digital finance is measured using the Digital Credit Index (*digital_credit*). It represents the development of the credit business carried out by Internet companies other than banks or other traditional financial institutions using digital technology. It is synthesized by AHP after the original data is processed without dimension.

3.3.3 Control variables

Based on existing literature, we control important factors that may affect the borrowing behaviors and operating conditions of family business, including the characteristics of the family and household head, the family's business, and economic environment in the city where the family lives. Characteristics of the household head include gender (*hh_gender*), age (*hh_age*), age square (*hh_age2*), marriage (*hh_marriage*), and education years (*hh_eduyears*). Characteristics of the family include family size (*family_size*), elderly dependency ratio (*old_ratio*), child dependency ratio (*young_ratio*), and total assets of the family (*family_asset*). Characteristics of the family's business[14] include total assets (*fmb_asset*), profit ratio (*fmb_proratio*), number of family members involved in production and management of the main business (*fmb_famnum*), and the length of time the family continues to control the business (*fmb_opeyears*). Characteristics of economic environment in the city where the family live include GDP per capita in the city (*city_ecolevel*). Considering that there may be extreme values of each variable, we have performed appropriate *Winsorize* treatments given the distribution of each variable (Table 1).

Table 2 displays the descriptive statistics for the variables under study. The average urban bank network density is 3.254 banks per 10,000 people, with a standard deviation of 1.686, revealing regional differences in traditional bank development are controllable. Similarly, the average digital credit index is 138.056, with a standard deviation of 38.154, indicating that the variation of digital credit development is within an acceptable level, with only a few regions showing very high values. For the household heads, the average age of is 47.467 years and the average education is 9.8 years. 82.2% of them are married or married or cohabiting. On average, the child dependency level is higher than that of elderly dependency in these families. The average operating life span of the SMFBs is 10.278 years, with a wide fluctuation ranging from 0 to 115 years, and typically, one family member manages the business.

3.4 Model specification

3.4.1 Tobit model for basic regression

Because our dependent variable *liabilities (liabilities_amo)* is left-censored at zero, with about 83.97% of the family businesses in the sample do not have industrial and commercial liabilities. Left-censoring means a data limitation (zero here) results in the liabilities clustering at a lower threshold. For this kind of data, multiple regressions and Logit or Probit model are inappropriate for the analyses. OLS estimates assume that the dependent variable is normally distributed. If the observations do not concentrate at certain values, multiple regressions would be useful. When there is such a concentration, the assumptions of multiple regressions are violated, and OLS would yield inconsistent estimates. Alternatively, if we treat the dependent variable as a dummy, where zero represents the samples without industrial and commercial liabilities and one represents the samples with liabilities, Logit or Probit model can be used. However, censored data is different from truncated data in that both limited and non-limited values provide useful information (Anastasopoulos et al., 2008). It is insufficient to throw away such information for the estimates. Furthermore, if we just use the

[14] For families running multiple businesses, we use the characteristics of the main business of the families. In our sample, 90.43% of families have only one business.

Table 1 Variables and settings

Types	Names of variables	Methods of computation
Dependent variables	*liabilities_amo*	Add 1 to the amount of industrial and commercial liabilities for households and take the logarithm.
Independent variables	*bank_density*	The total number of bank branches in the city/the average annual population of the city.
	digital_credit	The Digital Credit Index of PKU_DFIIC.
Characteristics of head of household	*hh_gender*	If the head of household is male, the variable equals to 1, otherwise the variable equals to 0.
	hh_age	The age of the head of household.
	hh_gender	If the head of the household is male, the variable equals to 1, otherwise the variable equals to 0.
	hh_marriage	If the head of the household is married or cohabiting, this variable is equal to 1, otherwise the variable equals to 0.
	hh_eduyears	The number of years of schooling of the head of household:illiteracy=0, primary school=6, junior high school=9, senior high school=12, technical secondary school or professional high school=13, junior college or higher vocational college=15, regular college=16, master degree=19, doctor degree=22.
Characteristics of family	*family_size*	Ln (number of people in the family+1)
	old_ratio	The number of seniors aged 65 and over in the household/the total number of people in the household.
	young_ratio	The number of children aged 14 and under in the household/the total number of people in the household.
	family_asset	Ln (total assets of the family+1)
Characteristics of family's main business	*fmb_asset*	Ln (total assets of the main business of the family+1)
	fmb_proratio	Profit of the main business of the family divided by gross revenue of the main business of the family.
	fmb_famnum	Ln (number of family members involved in production and management of the main business +1)
	fmb_opeyears	The year of survey minus the year when family started the main business.
Economic environment	*city_ecolevel*	Ln (GDP per capita in the city where the family lives+1)

samples with nonzero liabilities, it would result in serious sample selection bias in the estimated coefficients. Therefore, we choose Tobit model for our analyses in that it allows us to predict not only the probability of a family business to have industrial and commercial liabilities, but also the amount of liabilities the business has (Adesina & Zinnah, 1993). The Tobit model in this paper is expressed as follows:

$$Y_{1i} = \begin{cases} Y_{2i}, \text{if } Y_{2i} > 0 \\ 0 \ \ , \text{if } Y_{2i} \le 0 \end{cases} \tag{1}$$

$$Y_{2i} = \alpha + \beta x_i + \sum_{j=1}^{16} \gamma_{ij}\text{control}_{ij} + \text{year}_t + \text{city}_i + \text{industry}_i + \varepsilon_i \tag{2}$$

$i = 1, 2, \ldots, N$

where N is the number of samples, Y_{1i} is dependent variables, x_i is independent variables, and β is the parameters to be estimated. year_t is year fixed effect, city_i is city fixed effect, and industry_i is industry effect. ε_i is a normally and independently distributed error term with zero mean and constant variance σ^2 (Norris & Batie, 1987).

3.4.2 Heckman two-stage procedure for robustness test

Heckman (1979) thought that Tobit model may not be sufficient enough to take into account sample selection bias. He created a two-stage procedure to treat the

Table 2 Descriptive statistics of variables

Variable	Obs	Mean	Std. dev.	Min	Max
liabilities_amo	8625	1.975	4.283	0	12.899
bank_density	8625	3.254	1.686	0.406	8.064
digital_credit	8625	138.056	38.154	20.48	190.587
hh_age	8625	47.467	11.255	16	80
hh_age2	8625	2379.807	1100.36	256	6400
hh_gender	8625	0.822	0.382	0	1
hh_eduyears	8625	9.858	3.462	0	22
hh_marriage	8625	0.924	0.265	0	1
young_ratio	8625	0.149	0.170	0	0.500
old_ratio	8625	0.077	0.181	0	1
family_asset	8625	13.528	1.283	7.516	15.783
family_size	8625	1.511	0.316	0.693	2.197
fmb_proratio	8625	0.301	1.134	−6.999	1.143
fmb_asset	8625	10.623	2.755	0	14.604
fmb_famnum	8625	0.912	0.276	0	1.609
fmb_opeyears	8625	10.278	8.907	0	115
city_ecolevel	8625	11.09	0.790	9.544	13.095

selection bias problems of the nonrandomly selected samples. In the first step, Probit model is used to estimate the selection function. This yields the estimated lambda λ_i[15], which is the inverse of Mill's ratio, indicating the probability of being selected into the sample. In the second step, λ_i is used as a regressor in the main function by least squares on the subsamples to correct the sample censoring bias (Heckman, 1976).

We use Heckman two-stage procedure to conduct a robustness test. Following the model specifications, we first estimate the Probit function to determine whether a family with business has debts (function (3)). Then, we estimate the main function on *liabilities_amo,* the logarithm of the amount of commercial liabilities a family has (function (4)). In the selection function, in addition to using the same 14 control variables as in the previous regressions, an additional variable, the number of mobile phone users at the end of the year divided by the population of the city (*mob_tele*) is included. Because we think that access to the web can also influence whether residents can obtain loans. *mob_tele* reflects differences in digital technology development among regions, which captures the impact of digital divide on accessing digital finance. In the main function, 14 exogeneous variables the same as before are included.

$$Y_{1i} = X_{1i}\beta_1 + U_{1i} = \alpha_1 + \rho_1 x_i + \sum_{j=1}^{15} \gamma_{1ij}\text{control}_{ij} + \text{year}_t + \text{city}_i + \text{industry}_i + \varepsilon_{1i} \quad (3)$$

$$Y_{2i} = X_{2i}\beta_2 + U_{2i} = \alpha_2 + \rho_2 x_i + \rho_3\lambda_i + \sum_{j=1}^{14} \gamma_{2ij}\text{control}_{ij} + \text{year}_t + \text{city}_i + \text{industry}_i + \varepsilon_{2i} \quad (4)$$

where X_{1i} and X_{2i} are the vectors of exogenous regressors; β_1 and β_2 are the vectors of parameters. What is more

$$E(U_{mi}) = 0$$

$$E(U_{mi}U_{m'i''}) = \begin{cases} \sigma_{mm'}, & i = i'' \\ 0, & i \neq i'' \end{cases}$$

$$i = 1 \ldots I$$

4 Empirical results

4.1 Baseline results

This paper investigates the impacts of traditional finance and digital finance on the borrowing behavior and total debt amount of SMFBs. Column (1) of Table 3 shows the basic regression results of Tobit model that only controls the industry, city, and year fixed effects. As can be seen, the coefficient of network density of commercial banks is not significant, indicating that traditional finance has no effect on the debt behavior of SMFBs. The digital credit index is positively significant at the level of 5%, which suggests that development of digital finance promotes the debt behavior of SMFBs and increases their financial accessibility. We subsequently added new covariates to the basic regression and clustered the standard error at the household level. The result is presented in column (2). The density of bank branches is still not significant, and the digital credit index is positively significant. The result once again demonstrates

[15] It is a monotone decreasing function of the probability that an observation is selected into the sample (Heckman, 1979).

Table 3 The impact of traditional and digital finance on the liabilities of SMFBs

	(1) *liabilities_amo*	(2) *liabilities_amo*	(3) $\partial E(y \mid y>0,x)/\partial x$
bank_density	−1.857	−1.052	−0.199
	(−1.60)	(−0.76)	
digital_credit	0.121**	0.106**	0.020**
	(2.43)	(2.13)	
hh_age		0.437**	0.083**
		(2.55)	
hh_age2		−0.006***	−0.001***
		(−3.23)	
hh_gender		0.286	0.054
		(0.44)	
hh_eduyears		−0.167**	−0.032**
		(−1.97)	
hh_marriage		−1.945*	−0.368*
		(−1.90)	
young_ratio		4.007**	0.757**
		(2.30)	
old_ratio		0.168	0.032
		(0.09)	
family_asset		0.490*	0.093*
		(1.69)	
family_size		2.796***	0.528***
		(2.83)	
fmb_proratio		−2.010***	−0.380***
		(−12.30)	
fmb_asset		1.451***	0.274***
		(7.98)	
fmb_number		2.743***	0.519***
		(2.85)	
fmb_year		−0.311***	−0.059***
		(−8.78)	
city_ecolevel		−2.477	−0.468
		(−0.64)	
Industry	Y	Y	Y
City	Y	Y	Y
Year	Y	Y	Y
N	11997	8625	
Pseudo R^2	0.027	0.063	
Cluster		Household level	

Note: A Tobit model was conducted to examine the relationship between traditional and digital finance performance, using *bank_density* and *digital_credit* as proxies for traditional and digital finance, respectively, and *liabilities_amo* as the logarithm of business liabilities. The first column only controls the fixed effects of industry, city, and year, while the second column controls covariates on top of the first column and clusters standard errors at the household level. Furthermore, column (3) indicates that a unit increase in the digital credit index leads to a 2% rise in the scale of liabilities.

t statistics in parentheses

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$, the same for the following tables

that traditional finance cannot ease the credit constraints of SMFBs, while digital finance promotes not only the access to credit, but the amount of credit being accessed for SMFBs. Column (3) of Table 3 shows the average marginal effects of each variable on the actual loan amount of SMFBs. We can find that each unit increase in the digital credit index leads to a 2% increase in the scale of liabilities.

These results confirm that it is difficult for SMFBs to obtain financing from traditional finance. For one thing, as a remember of the small business clan, SMFBs share the disadvantages a typical SME has in terms of operation, management, and performance. These disadvantages create information asymmetry and transaction coast problems which make commercial banks unwilling and unable to lend to SMFBs. Although many believe that the use of financial technologizes by commercial banks may increase their capacities in providing loans to SMEs (Gomber et al., 2018; Livshits et al., 2016; Sutherland, 2018; Wang, 2015) and despite that various polices have been promoted by Chinese government to encourage commercial banks to finance SMEs, our results suggest that these developments have not provided significant incentives for commercial banks to help with SMFB's financing. For another, "As small and local banks may be more willing and able to reach small businesses (Berger & Udell, 2002; Stein, 2002), the underdevelopment of small and local banks in China maybe also contribute to this difficult situation for SMFBs' financing."

By contrast, digital credit business, carried out by Internet companies, can improve the financing conditions for SMFBs. It seems that digital financial institutions are more capable of reaching long-tail customers including SMFBs. More importantly, digital financial institutions may be more willing to serve SMFBs than traditional banks because their businesses are to a large extent designed to target the population excluded by the traditional financial market. For example, through the invention of the "310" model for lending, Ant Financial's MYbank developed by Alibaba has extended their credit business to more than 40 million small and micro businesses. Therefore, our hypothesis 1 is verified.

Characteristics of the business owner or family also exert significant impacts on SMFBs' financing, both in terms of the probability of getting a loan and the total amount of liabilities. The *hh_age* is positively significant, and the *hh_age2* is negatively significant, indicating that the rate of change in debt amount of small and micro family enterprises has an inverted U-shaped relationship with the age of the household head. but the inflection point is at 41.5 years old ($b/(-2a) = 0.083/[-2 \times (-0.001)] = 41.5$), That is, when the age of the household head is less than 41.5 years old, the change rate in liability amount of the SMFBs increases at a decreasing rate, and when the household head is older than 41.5, the change rate in liabilities decreases at an increasing rate. The coefficients for *hh_eduyears*, *hh_marriage*, *fmb_opeyears*, and *fmb_proratio* are all negatively significant, meaning that households with a married and better educated head are less likely to borrow, and the longer the family runs the business and the better the business performs, the less needs for loans. *family_size*, *famliy_asset*, *young*, *fmb_asset*, and *fmb_number* are positive significantly. Therefore, the larger the scale of household and business and more young people in the family, the higher the probability of getting loans.

4.2 Robustness checks

We further test the robustness of our results in three ways. (1) Change to use Heckman two-stage procedure. The results are shown in the first and second column of Table 4. As can be seen, controlling for selection bias, *digital_credit* is positively significant at 10% in the second stage, which confirms our previous findings. (2) Use a new digital divide variable to further control selection bias. We add the number of mobile phone users at the end of the year divided by the population of the city (*mob_tele*), and the result is shown in the third column. *digital_credit* is still positively significant. (3) Replace dependent variable. We replace *liabilities_amo* with a dummy variable which indicates whether small and micro enterprises have liabilities (*liabilities_dum*), the number of liabilities *(liabilities_num)*, and the proportion of liability amount to the total assets *(liabilities_rate)* of the company, and use Logit model for *liabilities_dum*. The results are shown in the fourth to the sixth column of Table 4. *digital_credit* is positively significant. (4) Replace independent variable. Regression is performed using the provincial digital credit index, and the results are in the last column of Table 4. It can be found that the province level *digital_credit-prov* is significantly positive at the 5% level. These results prove that the previous conclusions are robust.

4.3 Heterogeneity results

We further perform heterogeneity analyses for different subsamples. First, the samples are grouped by urban and rural areas for regressions. Columns (1) and (2) of Table 5 are the results for urban and rural households, respectively. It can be found that only *digital_credit* is significant at the 1% level in urban areas. In rural areas, neither independent variable is insignificant. It may due to the fact that urban residents are more capable of seeking external financing channels and more proficient in operating computers or smartphones, thus they can fully enjoy the benefits from digital credit services. By contrast, lacking financial and digital knowledge has made families in rural areas being excluded from both traditional and digital finance. For example, He et al. (2017) and Guo & Wang (2020) find that the use of digital finance by farmers is very limited because of their low level of financial knowledge reserve. As Hu et al. (2021) and Wang & Zhao (2020) observe, the existence of digital divide has led to a Matthew effect of digital finance on poverty reduction. While the development of digital finance reduces absolute poverty, it aggravates the relative poverty between urban and rural areas.

The last two columns of Table 5 are the regression results for SMFBs in the wholesale and retail industry and those in other industries, respectively. Wholesale and retail industry is the biggest sector in the service industry of China and a labor-intensive sector that plays a major role in providing employment opportunities.[16] The result in column (3) shows that *digital_credit* is positively significant at the 5% level for the liabilities of SMFBs in the wholesale and retail industry. Given the importance of SMFBs in the wholesale retail industry for economic development, employment, and life quality, the alleviation of their financing constraints by digital finance may generate huge positive outcomes.

The first two columns of Table 6 are regressions on the subsamples based on the profitability of SMFBs. The businesses whose total assets are higher than the median

[16] http://www.sic.gov.cn/News/455/8448.htm

Table 4 Robustness test

	(1) Heckman *liabilities_dum*	(2) Heckman *liabilities_amo*	(3) Tobit *liabilities_amo*	(4) Tobit *liabilities_rate*	(5) Tobit *liabilities_num*	(6) Logit *liabilities_dum*	(7) Tobit *liabilities_amo*
	First stage	Second stage					
bank_density	−0.162	−0.368	−1.551	−17.518	−0.291	−0.225	−0.997
	(−1.60)	(−1.52)	(−1.07)	(−1.16)	(−0.81)	(−1.17)	(−0.72)
digital_credit	0.007*	0.022*	0.113**	1.167**	0.021*	0.014**	
	(1.68)	(1.95)	(2.01)	(2.05)	(1.89)	(2.23)	
mob_tele	0.286*		2.965				
	(1.89)		(1.42)				
λ		0.852					
		(0.81)					
digital_credit-prov							0.118**
							(2.54)
Controls	Y	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y
N	8235	8229	8254	8292	8640	8597	8625
pseudo R^2	0.144		0.062	0.038	0.084	0.150	0.063
adj R^2		0.261					
Cluster	Household level	Household level	Household level	Household level	Household level	Household level	Household level

Note: Columns (1) and (2) present the results of the Heckman two-stage procedure. *liabilities_dum* represents whether a family have commercial debt, *liabilities_amo* is the logarithm of business liabilities, *bank_density* represents traditional finance by dividing the total number of bank branches in the city by the average annual population of the city, and *digital_credit* represents digital finance using the digital credit index from Peking University. The first stage shows that *digital_credit* has a positive and significant effect on households' abilities to gain liabilities. The second stage confirms that *digital_credit* can help SMFBs to obtain more loans. Column (3) uses the Tobit model, with a new control variable "the number of mobile phone users at the end of the year divided by the population of the city(*mob_tele*)". Columns (4)–(5) use the Tobit model, with *liabilities_rate* being the amount of industrial and commercial liabilities divided by total business assets, and *liabilities_num* being the number of industrial and commercial liabilities for households. Column (6) uses the Logit model to examine the dummy variable *liabilities_dum* representing whether a household business has liabilities. Column (7) uses the Tobit model but changes the independent variable from the city level to the province level. The robustness checks confirm the previous conclusions

$^{*}p < 0.1$, $^{**}p < 0.05$

are classified into the large-scale group, and the rest of the samples are classified into the small-scale group. For large-scale sample, only *digital_credit* is positively significant at the 10% level. For the small-scale group, both independent variables are insignificant. This may indicate that, even for SMFBs, relatively larger scale is helpful for them to obtain credit from digital finance.

The last two columns of Table 6 group the samples by management intensity of SMFBs. The median of the number of family members involved in the operation and management of the enterprise is used as the dividing point, as the samples above the median are classified into the strict management group, and the rest of the samples are classified into the loose management group. It can be found that the strict management group is more capable of enjoying the benefits from digital credit services. One possible explanation for this result is that, high level of family involvement in the operation and management of the business demonstrates the concern and devotion of the family has for the enterprise, and therefore serves as an indicator of good business performance for digital financial institutions.

Table 7 employs branch density of city commercial banks, rural commercial banks, state-owned banks,

Table 5 Grouped by the location and industry of SMFBs

	(1) Urban	(2) Rural	(3) Wholesale and retail industry	(4) Other industries
	liabilities_amo			
bank_density	−1.278	7.308	−4.505	−0.265
	(−0.86)	(1.52)	(−1.63)	(−0.17)
digital_credit	0.154***	0.045	0.211**	0.040
	(2.72)	(0.42)	(2.56)	(0.65)
Controls	Y	Y	Y	Y
Industry	Y	Y	Y	Y
City	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	6665	1960	3928	4697
r^2_p	0.069	0.093	0.073	0.076

Note: *bank_density* represents traditional finance, while *digital_credit* represents digital finance, and *liabilities_amo* is the logarithm of business liabilities. In columns (1) and (2), Tobit models are used on urban and rural samples, respectively. In column (3)-(4), the sample is divided into wholesale and retail industry and other industries.

$^{**}p < 0.05$, $^{***}p < 0.01$

joint-stock banks, and postal savings banks in each city as an explanatory variable for the regressions. Results indicate that all types of banks fail to significantly promote lending for SMFBs, indicating a collective reluctance to provide loan services to high-risk and low-benefit SMFBs. These findings suggest that policies aimed at promoting the willingness of commercial banks to finance small and micro enterprises over the past decade have not yielded desirable outcomes.

4.4 Extended research

Will increased access to credit help SMFBs with their business performance? This section explores the impacts of increased liabilities on SMFBs' operation and performance indicators. Column (1) of Table 8 uses the logarithmic form of the asset size (*business_ass*) of SMFBs as the explained variable for the regression, and excludes the asset size from the control variables. It can be seen that the *liabilities_amo* is significantly positive at the 1% level, indicating that the increase in financing for SMFBs helps them to expand their business size. Column (2) presents the regression coefficient on logarithm of business income (*business_incom*). The result shows that larger debt scale of SMFBs can increase the income. This may because the inflow of funds has improved the company's equipment and employee

Table 6 Grouped by the scale and management intensity of SMFBs

	(1) Large-scale	(2) Small-scale	(3) Strict-management	(4) Loose-management
	liabilities_amo			
bank_density	−0.548	−2.699	−0.313	−1.959
	(−0.37)	(−1.04)	(−0.16)	(−0.97)
digital_credit	0.112*	0.122	0.210***	−0.014
	(1.91)	(1.31)	(3.01)	(−0.19)
Controls	Y	Y	Y	Y
Industry	Y	Y	Y	Y
City	Y	Y	Y	Y
Year	Y	Y	Y	Y
N	4135	4490	4344	4281
Pseudo R^2	0.060	0.080	0.073	0.076
Cluster	Household level	Household level	Household level	Household level

Note: Table 6 presents results from a Tobit model. Bank density is used to represent traditional finance, and *digital_credit*, a digital credit index from Peking University, represents digital finance. The first two columns use large-scale and small-scale samples, respectively. Columns 3–4 separate samples into strict-management and loose-management based on the number of family members involved in the business

$^{*}p < 0.1$, $^{***}p < 0.01$

Table 7 Regressions by different types of banks

	(1)	(2)	(3)	(4)	(5)
	liabilities_amo				
city commercial bank_density	8.342				
	(1.27)				
rural commercial bank_density		−2.862			
		(−0.79)			
state-owned bank_density			−2.623		
			(−0.95)		
joint-stock bank_density				−2.935	
				(−0.65)	
postal savings bank_density					1865.579
					(0.34)
digital_credit	0.114**	0.113**	0.110**	0.098**	0.103**
	(2.24)	(2.19)	(2.18)	(1.94)	(2.07)
Controls	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
N	8625	8625	8625	8625	8625
Pseudo R^2	0.063	0.063	0.063	0.063	0.063
Cluster	Household level	Household level	Household level	Household level	Household level

Note: Table 7, which employs the Tobit model, examines the impact of bank branch density of different types of banks on SMFBs' lending. The independent variables are the density of city commercial banks, rural commercial banks, state-owned banks, joint-stock banks, and postal savings banks. *liabilities_amo* is the logarithm of business liabilities

$^{**}p < 0.05$

Table 8 Extended research

	(1)	(2)	(3)
	business_asset	*business_incom*	*profit_ratio*
liabilities_amo	0.081***	0.032***	−0.039***
	(13.99)	(5.42)	(−9.37)
Controls	Y	Y	Y
Industry	Y	Y	Y
City	Y	Y	Y
Year	Y	Y	Y
N	8586	8625	8625
adj. R^2	0.247	0.376	0.044
Cluster	Household level	Household level	Household level

Note: Table 8 based on Pooled OLS. *liabilities_amo* is the logarithm of business liabilities. *business_asset* is the logarithmic form of the asset size of the SMFBs. *business_incom* is the logarithm of income of SMFBs. *profit_ratio* is the proportion of enterprise profits to its income

$^{***}p < 0.01$

benefits, which enhances its operational capabilities. Column (3) uses the proportion of enterprise profits to its income (*profit_ratio*) of SMFBs as the explained variable for the regression. From the result, we can see that the increase of the debt scale of SMFBs has negative impact on their profitability. Therefore, to promote a sustainable development of SMFBs, there is more to do than just extending credit to them. Hypothesis 2 has been validated.

We further perform heterogeneity analyses by dividing the sample into four subgroups based on the physical address the SMFBs locate and the industry they belong to: the urban and rural groups, and the wholesale and retail industry and other industries, respectively. The regression coefficients for each group are presented in Tables 9 and 10. From the results, we can see that our findings concerning the impacts of increasing credits on SMFBs' business performance very consistent across different groups.

Table 9 Grouped by the location of the household—urban and rural

	(1) *Urban*	(2) *Rural*	(3) *Urban*	(4) *Rural*	(5) *Urban*	(6) *Rural*
	business_asset		*business_incom*		*profit_ratio*	
liabilities_amo	0.078***	0.081***	0.027***	0.048***	−0.040***	−0.035***
	(11.56)	(7.02)	(3.88)	(4.31)	(−8.18)	(−4.43)
Controls	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
N	6635	1951	6665	1960	6665	1960
adj. R^2	0.243	0.252	0.365	0.419	0.043	0.064
Cluster	Household level	Household level	Household level	Household level	Household level	Household level

Note: Table 9 based on Pooled OLS. *liabilities_amo* is the logarithm of business liabilities. *business_asset* is the logarithmic form of the asset size of the SMFBs. *business_incom* is the logarithm of income of SMFBs. *profit_ratio* is the proportion of enterprise profits to its income

***$p < 0.01$

Table 10 Grouped by the location of the household—wholesale and retail industry and other industries

	(1) Wholesale and retail industry	(2) Non-wholesale and retail industries	(3) Wholesale and retail industry	(4) Non-wholesale and retail industries	(5) Wholesale and retail industry	(6) Non-wholesale and retail industries
	business_asset		*business_incom*		*profit_ratio*	
liabilities_amo	0.079***	0.079***	0.022**	0.042***	−0.022***	−0.051***
	(9.16)	(9.85)	(2.43)	(5.39)	(−4.19)	(−8.37)
Controls	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
N	3915	4671	3928	4697	3928	4697
adj. R^2	0.218	0.271	0.342	0.409	0.031	0.062
Cluster	Household level	Household level	Household level	Household level	Household level	Household level

Note: Table 10 presents the results based on Pooled OLS with *liabilities_amo* as the logarithm of business liabilities and *business_asset*, *business_incom*, and *profit_ratio* as the logarithmic form of the asset size, income, and profitability of SMFBs, respectively

**$p < 0.05$, ***$p < 0.01$

5 Conclusions and implications

This paper investigates the roles of traditional finance and digital finance in the financing of SMFBs in China. Using the household-level data from China Household Financial Survey Project (CHFS), we conduct comprehensive and in-depth analyses on the current state of SMFBs' financing and how enhanced financing situation for SMFBs is associated with their business performance. The results from Tobit regression model show that traditional finance does not alleviate the financing constraints of SMFBs, while digital finance significantly promoted SMFBs' access to credit.

Additional credit from digital finance, however, can only help SMFBs with the increase of business scale and operational capability, but not their profitability. These findings provide new insights on the effectiveness of traditional financing and digital financing for SMFBs, which shed some lights on designing future lending policy to ease financial constraints of SMFBs.

The lack of support from traditional finance indicates that the digital transformation process that commercial banks are experiencing does not significantly promote their willingness in extending credit to SMFBs, even though it is generally believed that the use of advanced financial technologies will enable banks to overcome the information asymmetry problem and promote their capacities in lending to SMFBs. Neither do government policies appear to change the biases of commercial banks toward SMFBs. In the past decade, the National State Council, the People's Bank of China, the China Banking and Insurance Regulatory Commission, and the China Securities Regulatory Commission have issued important policies almost every year to encourage commercial banks to finance small and micro enterprises. But from our results, these polices do not seem to achieve their desired outcomes.

On the other hand, digital finance, especially digital credit business conducted by Internet companies, can significantly alleviate the financing constraints faced by SMFBs, which suggests that digital finance be an effective micro-loan provider who can enhance financial accessibility and broaden the coverage of financial services in China. The impact of digital finance is stronger for SMFBs located in urban areas, in the wholesale and retail industry, as well as for SMFBs with relatively larger scale and for firms where the owner's family members are more involved in business management. While increased access to loans from digital finance helps SMFBs to expand business scales and enhance operational capabilities, it decreases SMFBs' profitability, at least in the short run, mostly due to the high interest rates charged by digital financial institutions.

Based on these findings, our research has the following implications:

First, it is very important to incorporate the family-side characteristics of the business owner when studying small business financing, because many small business firms have a family ownership. For example, our finding suggests that to increase the likelihood of obtaining more loans, the family should take more responsibility for the enterprise. Involving more members from the owner family in the daily operation and management of the company is one useful way to achieve this goal.

Second, when trying to encourage commercial banks to lend to small and micro businesses, policymakers should bear in mind the profit-oriented nature of them. Subsidies may be necessary to protect banks' interests in order to motivate them to provide financial services to small and micro firms.

Third, to turn enhanced financing situation of SMFBs into profit growth and ensure their sustainable development, policymakers should take into account the affordability of digital financial services as they manage to promote financial inclusion through digital finance. It is critical for the government to regulate and monitor the real interest rates of digital financial services so as to prevent excessive costs that could harm the long-term operations and performance of SMFBs.

Finally, due to the limitations of the household survey data, we can only examine the short-term effect of digital finance on the firms' business performance. Future research should look into such impact over a longer time span in order to get a more complete understanding of how better access to loans from digital finance affects SMFB's development in the long run.

Appendix

Table 11 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *liabilities_amo*	1.000																
(2) *bank_density*	−0.090	1.000															
(3) *digital_credit*	−0.053	0.220	1.000														
(4) *hh_age*	−0.085	−0.140	0.055	1.000													
(5) *hh_age2*	−0.089	−0.129	0.052	0.989	1.000												
(6) *hh_gender*	0.009	−0.066	0.035	0.076	0.067	1.000											
(7) *hh_eduyears*	0.002	0.183	0.060	−0.387	−0.378	0.010	1.000										
(8) *hh_marriage*	0.018	−0.056	0.000	0.048	0.008	0.191	−0.025	1.000									
(9) *young_ratio*	0.106	−0.013	−0.022	−0.309	−0.291	0.007	0.072	0.110	1.000								
(10) *old_ratio*	−0.041	−0.067	0.003	0.389	0.439	0.031	−0.154	−0.059	−0.167	1.000							
(11) *family_asset*	0.077	0.219	0.135	−0.103	−0.106	0.015	0.322	0.051	0.066	−0.093	1.000						
(12) *family_size*	0.106	−0.150	−0.085	0.037	0.024	0.109	−0.131	0.279	0.450	−0.003	0.099	1.000					
(13) *fmb_proratio*	−0.151	0.000	−0.041	0.020	0.021	0.028	−0.022	0.013	−0.020	0.014	−0.006	−0.008	1.000				
(14) *fmb_asset*	0.173	0.088	0.030	−0.150	−0.150	−0.009	0.180	0.027	0.087	−0.080	0.425	0.060	0.013	1.000			
(15) *fmb_famnum*	0.048	−0.048	−0.021	0.046	0.041	0.046	−0.107	0.130	0.029	−0.024	0.042	0.202	0.002	0.126	1.000		
(16) *fmb_opeyears*	−0.121	−0.038	0.061	0.291	0.277	0.029	-0.086	0.041	-0.201	0.147	0.050	-0.073	0.106	-0.042	0.075	1.000	
(17) *city_ecolevel*	−0.109	0.857	0.309	-0.130	-0.118	-0.055	0.196	-0.039	-0.007	-0.064	0.258	-0.170	0.008	0.091	-0.061	-0.020	1.000

Table 12 Cluster at the industry and city level

	(1) *liabilities_amo*	(2) *liabilities_amo*
bank_density	−1.052	−1.052
	(−0.70)	(−0.83)
digital_credit	0.106**	0.106**
	(2.23)	(2.35)
hh_age	0.437**	0.437***
	(2.43)	(3.26)
hh_age2	−0.006***	−0.006***
	(−3.10)	(−4.26)
hh_gender	0.286	0.286
	(0.49)	(0.52)
hh_eduyears	−0.167*	−0.167**
	(−1.96)	(−2.01)
hh_marriage	−1.945**	−1.945**
	(−2.02)	(−1.99)
young_ratio	4.007**	4.007***
	(2.02)	(3.38)
old_ratio	0.168	0.168
	(0.09)	(0.10)
family_asset	0.490	0.490
	(1.62)	(1.56)
family_size	2.796**	2.796**
	(2.45)	(2.37)
fmb_proratio	−2.010***	−2.010***
	(−12.29)	(−8.11)
fmb_asset	1.451***	1.451***
	(7.25)	(9.26)
fmb_number	2.743***	2.743***
	(2.67)	(4.91)
fmb_year	−0.311***	−0.311***
	(−9.08)	(−11.09)
city_ecolevel	−2.477	−2.477
	(−0.60)	(−0.97)
Industry	Y	Y
City	Y	Y
Year	Y	Y
N	8625	8625
Pseudo R^2	0.063	0.063
Cluster	City level	Industry level

$p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Declarations

Conflict of interest The authors declare no competing interests.

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