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## Article

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China Journal of Accounting Studies (CJAS)

## Provided in Cooperation with:

Accounting Society of China (ASC), Beijing

*Suggested Citation:* Li, Xiaoxi; Zhong, Qinger; Yang, Guochao (2024) : Commercial bank digital transformation, information costs, and corporate financial constraints, China Journal of Accounting Studies (CJAS), ISSN 2169-7221, Taylor & Francis, Abingdon, Vol. 12, Iss. 1, pp. 140-163, <https://doi.org/10.1080/21697213.2024.2336094>

This Version is available at:

<https://hdl.handle.net/10419/338525>

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# Commercial bank digital transformation, information costs, and corporate financial constraints

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## ABSTRACT

The rapid development of digital finance has transformed traditional financial institutions. We investigate the effect and economic consequences of bank digital transformation on corporate financial constraints using data from China. The results show that bank digital transformation alleviates corporate financial constraints by decreasing information search, processing, and verification costs. Furthermore, the effect of bank digital transformation on corporate financial constraints is more pronounced for firms with higher contract intensity, more intangible assets, and poorer external information environment. We also find that bank digital transformation alleviates corporate financial constraints by increasing debt financing. In addition, we show that digital transformation promotes lending by big banks, resulting in the crowding-out effect. Finally, we find that bank digital transformation promotes the flow of credit resources to non-zombie firms, which effectively improves credit allocation efficiency. This paper extends research on digital finance and new structural finance from the perspective of bank digital transformation.

## KEYWORDS

Digital finance; commercial bank digital transformation; information costs; financial constraints

## 1. Introduction

The early lending market in China mainly comprised pawnshops, which required significant collateral and set extremely high interest rates (Li, 2002). During the Age of Discovery, the modern commercial bank began to take shape. The Industrial Revolution further stimulated the development of banking credit. The Information Revolution, which was marked by the invention and application of electronic computers, brought unprecedented changes to the banking industry. Economic changes and technological advances have caused the credit market to germinate, grow and then blossom, and the banking industry to evolve from manual bookkeeping to basic computerisation to the advanced use of information technology. However, neither traditional pawnshops nor modern commercial banks have fundamentally changed the basic tenet of using assets as collateral for loans.

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Paper accepted by Guliang Tang.

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With the current wave of digitalisation, data have become the fifth production factor adding to the well-established four: labour, land, knowledge, and technology. Data assets are the core assets of many emerging companies. However, despite their great value, there are no reliable accounting methods for measuring data assets. The inability of financial statements to reflect the actual value of data assets is a serious challenge for corporate valuation and has created a huge gap between the asset structure of many emerging companies and the collateral-based bank credit placement model. This, coupled with the fact that the lending decisions of commercial banks in China rely heavily on hard assets available for collateral (Qian et al., 2019), excludes companies with limited hard assets but high growth prospects from the financial market. This significantly restricts companies' incentives to innovate and develop. Accordingly, the inadequate supply of traditional financial services seriously constrains the transformation and high-quality development of the Chinese economy.

The gradual integration of digital finance methods and credit business could alleviate the mismatch between firms and credit resources. By using new technological tools such as information technology and big data in the credit approval process, banks could decrease the information search, processing, and verification costs and with better information, lending decisions would rely less on collateral (Cortina Lorente & Schmukler, 2018; Gong et al., 2021; Liang & Zhang, 2020; Sutherland, 2020; Zhang et al., 2021; Zhao & Tan, 2012). Specifically, banks can use these new technological tools to collect or obtain data on firms' e-commerce transactions, logistics, and settlements and on taxation, thus reduce information search costs. These technologies also allow banks to make efficient use of large datasets through data mining and feature extraction processes. They can create corporate portraits that can be used to judge corporate credit risks and approve credit limits, which helps to reduce information processing costs. In addition, digital supply chain finance systems combine the four flows (i.e. information flow, commercial flow, logistics, and capital flow) of business processes with the financing information chain, thus enhancing data credibility and reducing information verification costs.

In summary, bank digital transformation may alleviate information asymmetry between banks and companies by decreasing information search, processing, and verification costs, and thus alleviating corporate financial constraints. For example, Zhao and Tan (2012) find that e-commerce platforms reduce information asymmetry between banks and companies, thereby alleviating the mismatch of credit resources. Gong et al. (2021) show that digital supply chain financial services help banks to obtain high-quality verifiable information, which improves credit allocation efficiency. However, digital finance may also lead to risk-taking behaviours of banks through scale effects and competition effects (Dai & Fang, 2014; Guo & Shen, 2019; Qiu et al., 2018), reducing resource allocation efficiency and exacerbating corporate financial constraints. Thus, the effects of bank digital transformation on corporate financial constraints in the context of digital finance remain an empirical question.

To investigate the impact of bank digital transformation on corporate financial constraints, we use the Bank Digital Transformation Index data from the Institute of Digital Finance at Peking University and hand-collected bank loan data of Chinese listed companies to construct bank digital transformation indicators at the firm level. Our findings are as follows. First, bank digital transformation can alleviate corporate financial

constraints. We get similar results when using three subs-indices of bank digital transformation (organisational, product, and cognitive), and taking into consideration potential measurement errors, omitted variables, and other endogeneity issues. Second, the effect of bank digital transformation on corporate financial constraints is more pronounced for firms with higher contract intensity, more intangible assets, and a poorer external information environment. Furthermore, bank digital transformation alleviates corporate financial constraints through increasing debt financing rather than lowering financing cost. Third, digital transformation promotes lending by big banks, resulting in the crowding-out of smaller banks. That is, digital transformation reinforces the information advantage of big banks. Finally, digital transformation drives banks to provide loans to non-zombie firms, contributing to improved credit allocation efficiency.

The main contributions of this paper are as follows. First, our study contributes to the digital finance literature by exploring the impact of banks' implementation of digital finance tools on corporate financial constraints. Prior research on digital finance mainly focuses on P2P lending, equity crowdfunding, and mobile payments (Li & Shen, 2019; Liao et al., 2014; Mollick, 2014; Tang, 2019; Vallee & Zeng, 2019; Wang & Huang, 2018). Unlike P2P lending, equity crowdfunding, and mobile payments, which mainly serve individuals and micro and small enterprises, bank loans are the most important source of external financing for firms in China.<sup>1</sup> Therefore, understanding the impact of digital finance on the real economy in China requires a full consideration of its impact on banks, which play a dominant role in the Chinese financial system. However, there are few studies on the effects of banks' implementation of digital finance. Thus, our study expands the digital finance literature by showing that bank digital transformation can narrow the information gap between banks and companies and hence alleviate corporate financial constraints.

Second, our study re-examines the potential changes in the market structure of the banking industry in a digital economy. A common assumption is that under new structural finance, optimal banking structures vary between countries based on a country's stage of development (Lin & Li, 2001; Zhang et al., 2019). The logic of this assumption is that small banks have better access to soft information in local credit markets than big banks and thus perform better in servicing small business credit needs. However, technological developments may change the way banks overcome information asymmetry, altering the comparative advantages of big and small banks. We find that bank digital transformation significantly increases the marginal gains of big banks in processing soft information, thereby challenging the information advantage of small and medium-sized banks in local credit markets and resulting in a crowding-out effect. Therefore, by identifying the impact of digital transformation on banks' credit operations, our study further enriches the literature on new structural finance.

Finally, our findings have some practical value. How to improve the credit allocation efficiency of traditional financial markets and effectively ease corporate financing woes are important issues in China's financial reform. Thus, our study, showing the positive effect of the digital transformation of banks on the efficiency of credit resource allocation,

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<sup>1</sup>By the end of 2020, China's banking industry assets (RMB319.74 trillion) accounted for 90.5% of the country's total financial industry assets (RMB353.19 trillion) (data from the People's Bank of China. The share of total banking industry assets in the country's total financial assets far exceeds that of countries with similarly bank-dominated financial systems, such as Japan and Germany.

has important implications for policymakers seeking to effectively alleviate corporate financial constraints.

The remainder of this paper is organised as follows. [Section 2](#) introduces the institutional background and hypothesis development. [Section 3](#) describes the research design. [Section 4](#) discusses our main results. [Section 5](#) presents additional analysis, and [Section 6](#) concludes the study.

## 2. Institutional background and hypothesis development

### 2.1. Institutional background

We use the Bank Digital Transformation Index data from the Institute of Digital Finance at Peking University to measure the digital transformation of commercial banks in China. This index, which started in 2010, has been used to analyse the digital transformation of commercial banks in China (Wang & Xie, 2021). It collects texts and financial data from the annual reports of 228 banks, including 6 large state-owned commercial banks, 12 joint-stock commercial banks, 121 urban commercial banks, 51 rural commercial banks, 24 foreign banks, and 14 private banks. As of the end of 2018, these banks held 98.35% of the total assets of commercial banks in China. Thus, the banks in this index system are reliable representatives of China's commercial banks.

[Figure 1](#) illustrates the three dimensions used to construct the Bank Digital Transformation Index: cognition, organisation, and product. Cognition, as a precursor to behaviour, is the commercial bank's awareness, understanding, and attention to the technological changes associated with digital finance. Thus, a higher score on the cognitive sub-index indicates a higher likelihood that a bank uses digital technology to transform and upgrade its financial services. Organisational reforms help banks implement digital finance transformation effectively and successfully, as the ability of commercial banks to innovate, execute, and integrate their business strategies is dependent on their internal structure. In particular, setting up a professional digital finance department is vital for laying out and coordinating related processes. For example, commercial banks can establish a Fintech committee at the head office to help the whole bank formulate appropriate development strategies. Finally, for the product dimension, integrating digital technology and financial products helps banks customise their financial services and provide added value to companies.

The Bank Digital Transformation Index consists of three sub-indices, representing the three dimensions. The cognitive sub-index measures the frequency of keywords related to digital finance in commercial banks' annual reports, such as Fintech, technology finance, and cloud computing. The organisational sub-index captures whether commercial banks have carried out relevant organisational reforms, such as setting up digital transformation-related departments, hiring IT executives or directors, and cooperating with digital finance companies. The product sub-index measures whether commercial banks have launched products such as mobile banking, WeChat banking, online loans, or e-commerce.

[Figure 2](#) illustrates the changes in the Digital Transformation Index and sub-indices scores of commercial banks in China from 2010 to 2018. As shown in the figure, the digital transformation of banks in China has steadily increased over this period, with the index

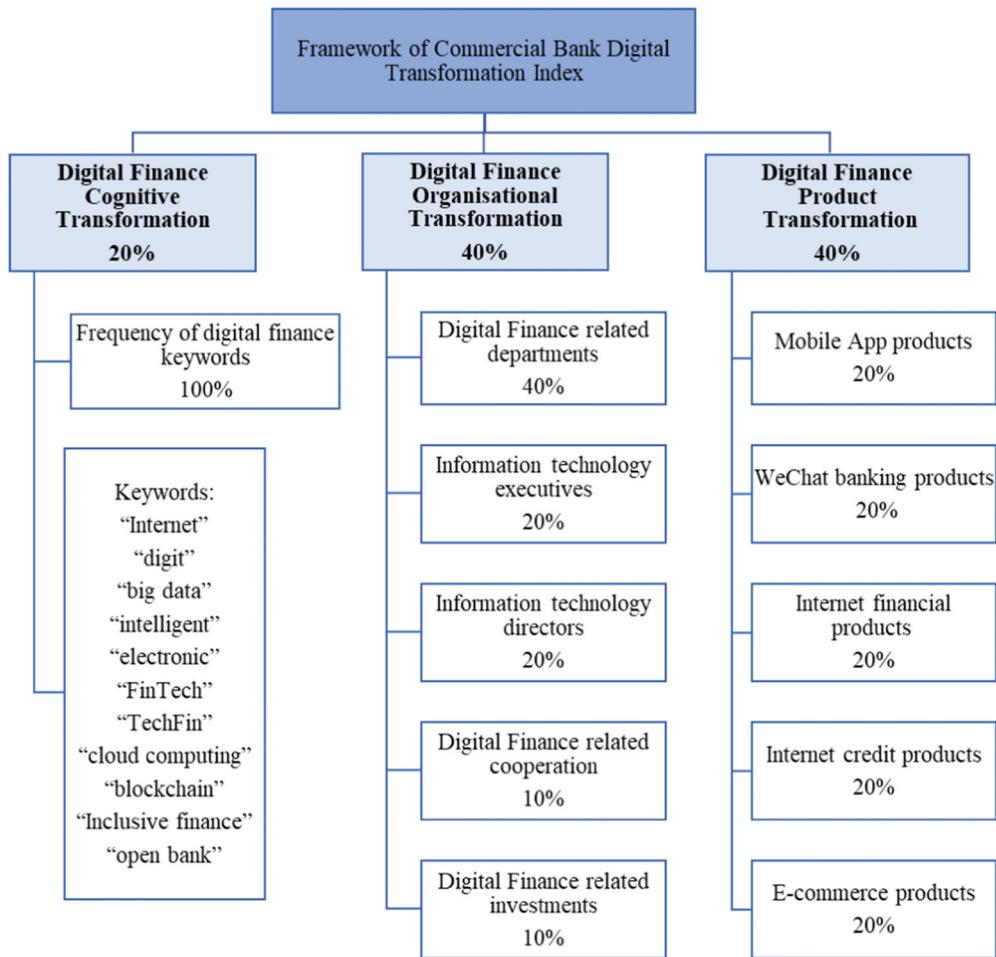
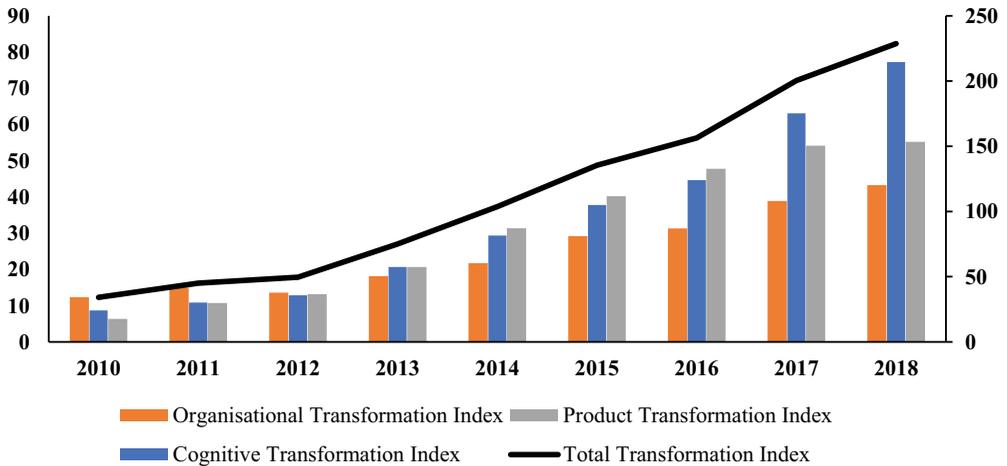


Figure 1. Framework of Commercial Bank Digital Transformation Index.

score rising from 12.28 in 2010 to 82.32 in 2018. Furthermore, after the introduction of Internet finance in 2013 and the establishment of the Fintech Committee by the People’s Bank of China (PBC) in 2017, the speed of this digital transformation substantially increased.

## 2.2. Hypothesis development

The rise of the digital economy has not only challenged banks’ reliance on collateral to make lending decisions but has also changed the incentives for banks to gather and generate information. Specifically, before the emergence of the digital economy, collateral was a necessary and sufficient condition for banks’ lending decisions, resulting in a lack of incentives for banks to collect costly information. Gorton and Ordonez (2014) find that banks are reluctant to collect and generate information when the perceived quality of collateral is high, which is common in China’s banking system due to its excessive emphasis on collateral (Song et al., 2011). However, in the digital economy, business



**Figure 2.** The Digital Transformation Index and sub-indices of commercial banks from Peking University. Note: The left axis shows the Digital Transformation Index, the organisational sub-index, and the product sub-index; the right axis shows the cognitive sub-index.

modes are gradually changing, and firms often lack tangible assets, which is forcing banks to make substantial changes to collect information to avoid losing customers.

We examine the impact of bank digital transformation on corporate financial constraints from the perspective of information search, processing, and verification costs. First, digital transformation helps decrease banks' information search costs. Digital technology can provide easy access to multiple dimensions of information (Berg et al., 2020; Goldstein et al., 2019; Liberti & Petersen, 2019; Xie & Zou, 2012; Zhu, 2019), such as real-time operational data (e.g. e-commerce transactions and logistics) and external information (e.g. taxation). For example, Zhao and Tan, (2012) show that banks can use e-commerce platforms to collect information on firms' business and transactions, as well as information about peer firms for comparative analysis of investment risks. Zhu (2019) shows that big data, including satellite images, provide granular indicators of fundamentals and thus help banks to predict firms' future profitability. Liberti et al. (2022) find that information sharing helps banks improve access to credit and build relationships with high-quality borrowers. Therefore, digital technology helps reduce information asymmetry between banks and firms by decreasing information search costs.

Second, digital transformation helps decrease banks' information processing costs. Digital technologies such as blockchain, cloud computing, and artificial intelligence can efficiently process massive amounts of data, thereby reducing banks' information processing costs. Information in traditional bank databases is uncoded and unstructured, and each project constitutes a separate data set. Thus, it is difficult for banks to integrate, process, and analyse these data. In contrast, using data mining techniques, banks can transform raw data into useful information that can directly improve lending decisions, resulting in a better assessment of a company's creditworthiness. For example, Barboza et al. (2017) and Jiang et al. (2018) find that machine learning can help banks predict corporate bankruptcy risk. Lee et al. (2019) construct an analytical framework that includes FinTech, information frictions, and financing gaps, and find that both information

processing technology and information collecting technology can help banks identify firm quality and thus close the financing gap by lowering the probability of the misclassification of good firms as bad firms. Therefore, bank digital transformation helps reduce information asymmetry between banks and firms by decreasing information processing costs.

Third, digital transformation helps decrease banks' information verification costs by cross-validating data. Before the emergence of the digital economy, banks generally verified the reliability of a company's financial information through offline due diligence. In contrast, the multi-dimensional information obtained by digital technologies makes it easier to certify the reputation and trustworthiness of firms. For example, digital supply chain finance enhances data credibility by combining the four flows in business processes (i.e. information flow, commercial flow, logistics, and capital flow) with upstream information. Gong et al. (2021) note that digital supply chain financial services help banks to obtain high-quality verifiable information, thereby improving credit allocation efficiency. Bushman et al. (2017) find that media coverage of borrowers can reduce information asymmetry not only between lenders and borrowers but also within a bank syndicate, thus attracting more non-relationship lenders to participate in loan syndication and reducing the cost of debt. Therefore, bank digital transformation helps reduce information asymmetry between banks and firms by decreasing information verification costs.

Furthermore, in the ex-ante screening process, digital tools help banks to improve the assessment of corporate creditworthiness by building algorithms that harden corporate soft information and processing big data (Sutherland, 2018, 2020; Tang et al., 2020). Digital transformation also improves banks financial services by allowing them to customise financial services to meet borrowers' specific financial needs. In the ex-post monitoring process, digital transformation helps banks improve credit risk management (Sutherland, 2020; Tang et al., 2020). For example, digital tools help banks to monitor the actions of borrowers and prevent high-risk borrowers from engaging in high-risk investments. Thus, bank digital transformation can decrease information asymmetry and improve credit allocation efficiency, and this alleviates firms' financial constraints. This leads to our main hypothesis.

**H1:** Bank digital transformation is negatively associated with corporate financial constraints.

### 3. Research design and sample selection

#### 3.1. Research design

Following the previous literature (e.g. Custódio & Metzger, 2014; Fazzari et al., 1988; Jiang et al., 2019), we construct the following model using firm-year observations.

$$INV_{i,t} = \alpha_0 + \alpha_1 BF_{i,t-1} + \alpha_2 CF_{i,t} + \alpha_3 BF_{i,t-1} * CF_{i,t} + \delta X_{i,t} + \beta Z_{c,t} + \eta_i + \varphi_t + \varepsilon_{i,t} \quad (1)$$

where  $INV_{i,t}$  is the ratio of investment to assets for firm  $i$  in city  $c$  and year  $t$ , is measured as the capital expenditure scaled by lagged total assets. And cash flow ( $CF$ ) is measured as the net cash flow from operating activities scaled by lagged total assets. The independent variable  $BF_{i,t}$  is the weighted digital transformation index (*BankTech*) or sub-indices (*BankOrg*, *BankPduc*, or *BankCon*) of the banks that lend to firm  $i$  in year  $t$ . To construct

a weighted bank digital transformation index at the firm-year level, we use the Commercial Bank Digital Transformation Index data from the Institute of Digital Finance at Peking University and employ firm-year-bank observations where a lending relationship exists:

$$BF_{i,t} = \sum BF_{j,t} * Ratio_{ij,t} \quad (2)$$

where  $BF_{j,t}$  is the digital transformation index or sub-indices for bank  $j$  in year  $t$  and  $Ratio_{ij,t}$  is defined as the proportion of the loans provided by bank  $j$  to the sum of bank loans based on hand-collected bank loan information. To mitigate potential endogeneity issues, we use a one-period lag of bank digital transformation in equation (1). Meanwhile, to facilitate interpretation of regression coefficients, we use standardised digital transformation index or sub-indices as independent variables.

We follow Custódio and Metzger (2014) and Jiang et al. (2019) to include the following firm-level control variables ( $X$ ): first, firm ownership characteristics: whether or not the firm is a state-owned enterprise (*SOE*); second, financial indicators: size (*SIZE*), leverage (*LEV*), growth (*TobinQ*), performance (*OPROA*), the proportion of fixed assets (*PPE*); third, corporate governance: shareholding of the first largest shareholder (*FIRST*), board independence (*INDP*). We also include region-level control variables ( $Z$ ), including: marketisation level (*MktIndex*), regional GDP growth rate (*GDPG*) and GDP per capita (*GDPPer*).  $\eta_i$  and  $\varphi_t$  are firm and year fixed effects. We expect  $\alpha_3$  is expected to be significantly negative. Table 1 shows the variable definitions. And we follow Petersen (2009) to use the standard errors clustered at the firm level.

### 3.2. Sample selection and descriptive statistics

#### 3.2.1. Sample selection

Our sample includes A-share non-financial listed firms from 2011 to 2019. The key variable of interest is the degree of bank digital transformation, which is measured using the Commercial Bank Digital Transformation Index data from the Institute of Digital Finance at Peking University (Wang & Xie, 2021). We manually collect information on material bank loans disclosed in annual reports and interim announcements of listed companies to obtain detailed firm-year-bank loan information, and other financial data are obtained from the China Stock Market & Accounting Research Database (CSMAR).

The sample selection process is as follows. First, we delete observations where the name of the bank or the amount of bank loans is missing. Second, we delete observations with missing bank digital transformation indices. Third, we exclude financial firms. This process leaves us with a final sample of 9,437 firm-year observations.

#### 3.2.2. Summary statistics

Table 2 reports the summary statistics. We winsorise all continuous variables at the 1<sup>st</sup> and 99<sup>th</sup> percentiles. According to Table 2, the mean value of firm investment level (*INV*) is 0.06 and the mean value of cash flow (*CF*) is 0.04, which is consistent with the results of Jiang et al. (2016). The mean value of bank digital transformation index (not standardised) (*BankTech*) is 76.20.

**Table 1.** Variable definitions.

Variables	Definitions
Corporate financial constraints	
<i>INV</i>	Corporate investment, the capital expenditure scaled by the lagged total assets. Capital expenditure is calculated as follow: Cash paid to acquire fixed assets, intangible assets and other long-term assets + Cash paid to acquire subsidiaries and other business entities – Cash from disposing of fixed assets, intangible assets and other long-term assets – Cash from disposing of subsidiaries and other business entities – Depreciation of fixed assets – Amortisation of intangible assets – Deferred expenses.
<i>CF</i>	Cash flow, computed as the net cash flow from operating activities scaled by lagged total assets.
Bank digital transformation	
<i>BankTech</i>	The degree of bank digital transformation, the Bank Digital Transformation Index weighted by the loan amount at the firm-year level.
<i>BankOrg</i>	The organisational dimension of Bank Digital Transformation Index.
<i>BankPduc</i>	The product dimension of Bank Digital Transformation Index.
<i>BankCon</i>	The cognitive dimension of Bank Digital Transformation Index.
Control variables	
<i>SOE</i>	An indicator equal to one if the firm is an SOE, and 0 otherwise.
<i>SIZE</i>	The logarithm of the total market capitalisation of the company.
<i>LEV</i>	Corporate leverage, total liabilities divided by total assets.
<i>TobinQ</i>	Ratio of the market value of equity to the book value of equity.
<i>OPROA</i>	Company performance, operating profits divided by total assets.
<i>PPE</i>	The proportion of fixed assets, fixed assets divided by total assets.
<i>FIRST</i>	Ownership of the first largest shareholder.
<i>INDP</i>	Board independence, the proportion of independent directors.
<i>MktIndex</i>	Total marketability index.
<i>GDPG</i>	GDP growth rate of the city where the company is located.
<i>GDPPER</i>	The logarithm of GDP per capita in the city where the company is located.

**Table 2.** Summary statistics.

Variables	Mean	Median	SD	P25	P75
<i>INV</i>	0.06	0.04	0.08	0.01	0.09
<i>CF</i>	0.04	0.04	0.08	0.00	0.09
<i>BankTech</i>	76.20	77.60	52.50	36.10	109.60
<i>BankOrg</i>	39.40	41.00	26.20	20.30	57.30
<i>BankPduc</i>	58.80	69.40	35.60	28.50	89.20
<i>BankCon</i>	184.60	153.00	162.20	54.10	268.50
<i>SOE</i>	0.34	0.00	0.47	0.00	1.00
<i>SIZE</i>	15.33	15.27	0.91	14.69	15.90
<i>LEV</i>	0.47	0.47	0.20	0.32	0.62
<i>TobinQ</i>	2.71	2.09	1.95	1.44	3.22
<i>OPROA</i>	0.03	0.03	0.08	0.01	0.06
<i>PPE</i>	0.20	0.17	0.16	0.08	0.29
<i>FIRST</i>	0.33	0.30	0.14	0.22	0.42
<i>INDP</i>	0.38	0.36	0.06	0.33	0.43
<i>MktIndex</i>	8.25	9.14	1.67	7.07	9.77
<i>GDPG</i>	0.09	0.09	0.06	0.07	0.12
<i>GDPPER</i>	11.41	11.51	0.51	11.09	11.82

## 4. Empirical results

### 4.1. The impact of bank digital transformation on corporate financial constraints

The regression results of equation (1) are shown in Table 3. Column (1) of Table 3 shows that the coefficient on the interaction term  $BF*CF$  is  $-0.041$  and significantly negative at the 5% level, indicating that bank digital transformation helps to reduce corporate investment-cash flow sensitivity. Columns (2)-(4) of Table 3 present the results on the

**Table 3.** Effects of bank digital transformation on corporate financial constraints.

	(1)	(2)	(3)	(4)
	<i>INV</i>	<i>INV</i>	<i>INV</i>	<i>INV</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*CF</i>	<b>-0.041**</b> <b>(-2.27)</b>	<b>-0.043**</b> <b>(-2.23)</b>	<b>-0.041**</b> <b>(-2.21)</b>	<b>-0.033*</b> <b>(-1.95)</b>
<i>BF</i>	0.001 (0.75)	0.002 (1.07)	0.001 (0.47)	0.001 (0.63)
<i>CF</i>	0.075*** (3.80)	0.078*** (3.90)	0.078*** (3.91)	0.075*** (3.78)
<i>SOE</i>	-0.002 (-0.29)	-0.002 (-0.24)	-0.002 (-0.28)	-0.002 (-0.29)
<i>SIZE</i>	0.004 (1.20)	0.004 (1.12)	0.004 (1.12)	0.004 (1.23)
<i>LEV</i>	0.028* (1.83)	0.029* (1.87)	0.028* (1.83)	0.028* (1.82)
<i>TobinQ</i>	0.003** (2.00)	0.003** (2.06)	0.003** (2.03)	0.003* (1.96)
<i>OPROA</i>	0.086*** (4.27)	0.084*** (4.19)	0.085*** (4.21)	0.086*** (4.28)
<i>PPE</i>	-0.114*** (-5.26)	-0.114*** (-5.26)	-0.114*** (-5.24)	-0.114*** (-5.27)
<i>FIRST</i>	0.025 (1.02)	0.025 (1.04)	0.025 (1.01)	0.025 (1.02)
<i>INDP</i>	-0.043 (-1.38)	-0.043 (-1.37)	-0.043 (-1.39)	-0.043 (-1.38)
<i>MktIndex</i>	0.006 (1.50)	0.006 (1.47)	0.006 (1.50)	0.006 (1.50)
<i>GDPG</i>	-0.004 (-0.23)	-0.004 (-0.23)	-0.004 (-0.24)	-0.004 (-0.22)
<i>GDPPER</i>	0.001 (0.05)	0.000 (0.02)	0.001 (0.07)	0.000 (0.03)
<i>Constant</i>	0.001 (0.00)	0.007 (0.05)	0.001 (0.00)	0.002 (0.01)
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R<sup>2</sup></i>	0.329	0.329	0.329	0.329

The *t*-statistics, calculated using robust standard errors clustered at the firm level, are reported in parentheses. \*, \*\*, and \*\*\* represent significance at the 10%, 5%, and 1% levels, respectively. The same as below.

three sub-indices, which is consistent with that in column (1). Therefore, the above evidence shows that bank digital transformation helps to alleviate corporate financial constraints and supports H1.<sup>2</sup>

## 4.2. Robustness tests

### 4.2.1. Endogeneity tests to solve the problem of measurement error

The bank digital transformation index is correlated with bank characteristics (e.g. size) and may reflect their ability to provide service to firms, suggesting that there may exist measurement error in constructing *BF*. Specifically, larger banks are more likely to serve larger firms with less financial constraints. Meanwhile, larger banks are more likely to pursue digital transformation. As a result, firms with less financial constraints are more likely to have a higher degree of *BF*. To address the measurement error, we use the

<sup>2</sup>Alternatively, we use WW Index as the dependent variables and get similar results. We dropped this exercise for brevity.

**Table 4.** Endogeneity tests to solve measurement error issue.

	(1)	(2)	(3)	(4)
	INV	INV	INV	INV
	BF = BankTech	BF = BankOrg	BF = BankPduc	BF = BankCon
<i>Resid_BF*CF</i>	<b>-0.083**</b> <b>(-2.09)</b>	<b>-0.162*</b> <b>(-1.78)</b>	<b>-0.165**</b> <b>(-2.36)</b>	<b>-0.031*</b> <b>(-1.88)</b>
<i>Resid_BF</i>	0.001 (0.12)	0.008 (1.10)	-0.006 (-0.73)	0.001 (0.41)
<i>CF</i>	0.078*** (3.90)	0.077*** (3.83)	0.079*** (3.97)	0.075*** (3.79)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R<sup>2</sup></i>	0.329	0.329	0.329	0.329

residual from regressing digital transformation index on bank fundamental characteristics. That is, we use bank-year data and regress bank digital transformation on bank fundamental characteristics, including total assets (*BankSIZE*), performance (*BankROA*) and leverage (*BankLEV*) to obtain the residual, and further construct a firm-year weighted index (*Resid\_BF*).

The corresponding regression results are reported in Table 4. After ruling out the effect of bank fundamental characteristics, we still get similar results.

#### 4.2.2. Endogeneity tests to solve the problem of omitted variables

The results in the main test may be due to omitted variables. On the one hand, regional digital finance development helps complement traditional finance and improve access to credit (Tang et al., 2020; Xie et al., 2018), then the decrease in corporate financial constraints is likely to result from increase in digital finance development in the city where the company is located rather than from bank digital transformation. On the other hand, some unobservable time factors may simultaneously lead to an increase in bank digital transformation and a decrease in corporate financial constraints. Thus, we address the above omitted variable problems by adding the regional digital finance development level and its interaction term with cash flow (*CF*), and the interaction term of cash flow with time trends, respectively. The regression results (not tabulated for brevity) corroborate the OLS estimates.<sup>3</sup>

#### 4.2.3. Instrumental variable test

Unobservable firm characteristics may simultaneously lead to less financial constraints and easier access to loans from banks with higher levels of digital transformation, such as, the implicit government guarantees. To address the endogeneity concern, we then introduce the following instrument variables: first, the proportion of the labour receiving formal IT training and the proportion of employees who regularly use computers (*IT\_Index*), from the 'Government Governance, Investment Environment and Harmonious Society: Improving the Competitiveness of 120 Chinese Cities' published by the World Bank in 2006; second, the ranking of 'Computer Science and Technology' department of the universities in the city

<sup>3</sup>The results are available upon request.

where the bank is incorporated (*College20*). Specifically, according to the 2007–2009 ‘Computer Science and Technology’ rankings released by China Academic Degree and Graduate Education Development Center, *College20* takes the value of one if a top 20 university for computer science is located in the city where the bank is incorporated, and zero otherwise.

On one hand, a city with many employees who have received formal IT training provides sufficient human capital for banks to develop digital technology. Similarly, the development of computer science in the city can lead to improvement in technology and increase in its talent, thus promoting bank digital transformation. On the other hand, corporate financial constraints are determined by their business decisions and financial development in the city and are unlikely to be directly affected by the IT index or the availability of top 20 universities for computer science.

Further, following the previous literature (e.g. Braggion et al., 2017; Mukherjee et al., 2017), we run a first-stage regression based on bank-year data, i.e. regressing bank digital transformation index on instrumental variables, with control variables including: total bank assets (*BankSIZE*), bank performance (*BankROA*), bank leverage (*BankLEV*), regional bank competition (*HHI*), regional informatization (*CityTech*), the share of tertiary sector (*Third*), regional marketisation (*MktIndex*), regional GDP growth (*GDPG*) and GDP per capita (*GDPPER*). Specifically, *HHI* is measured as the opposite number of the shares of top three banks in the city, and *CityTech* is measured as the proportion of mobile phone users per one hundred people. Then, the fitted value (*BankTech\_hat*) from the first-stage regression is used in the second-stage regression. Column (1) of Table 5 shows that, the coefficients on the two instrumental variables in the first-stage regression are significantly positive. Column (2) of Table 5 shows that the results of the second-stage regression are consistent with the OLS estimates.

### 4.3. Cross-sectional tests

#### 4.3.1. Corporate contract intensity

High contract intensity usually indicates that the transaction is exclusive, inimitable, or even irreplaceable, such as human capital contracts and technology transfer contracts. As a result, contract-intensive transactions often lack an open market, which makes it difficult for outsiders, such as banks, to get reference prices for these transactions. As a result, it is difficult to obtain and verify information for firms with higher contract intensity, thus weakening their financing ability. Digital technology, with its information searching and processing advantages, helps banks to obtain information and deal with the complex information environment, and thus effectively reduces the information asymmetry between banks and highly contract-intensive firms. Therefore, we expect that the effect of bank digital transformation on corporate financial constraints is more pronounced for firms with higher contract intensity.

We estimate the following model, where *Group* is a dummy variable for more contract-intensive firms (*MoreContract*). Specifically, we follow Nunn (2007) to measure industry contract intensity by using information on intermediate inputs in the input-output table, and *MoreContract* takes the value of one if the industry contract intensity which the firm belongs to is in the top tercile of the sample and zero otherwise.

**Table 5.** Instrumental variable test.

	(1)		(2)
	First stage		Second stage
	<i>BankTech</i>		<i>INV</i>
<i>IT_Index</i>	0.242** (2.05)	<i>BankTech_hat*CF</i>	-0.045** (-2.36)
<i>College20</i>	0.065** (2.04)	<i>BankTech_hat</i>	0.001 (0.86)
<i>BankSIZE</i>	0.110*** (10.62)	<i>CF</i>	0.076*** (3.85)
<i>BankROA</i>	-0.475 (-1.36)	<i>SOE</i>	-0.002 (-0.27)
<i>BankLEV</i>	-1.607 (-0.46)	<i>SIZE</i>	0.004 (1.17)
<i>HHI</i>	-0.129 (-0.81)	<i>LEV</i>	0.028* (1.84)
<i>CityTech</i>	0.215*** (6.16)	<i>TobinQ</i>	0.003** (2.03)
<i>Third</i>	-0.665*** (-4.80)	<i>OPROA</i>	0.086*** (4.24)
		<i>PPE</i>	-0.114*** (-5.26)
		<i>FIRST</i>	0.025 (1.03)
		<i>INDP</i>	-0.043 (-1.38)
<i>MktIndex</i>	0.005 (0.79)	<i>MktIndex</i>	0.006 (1.52)
<i>GDPG</i>	0.204 (0.87)	<i>GDPG</i>	-0.004 (-0.21)
<i>GDPPER</i>	-0.051 (-1.57)	<i>GDPPER</i>	0.001 (0.07)
<i>Constant</i>	-1.833*** (-4.02)	<i>Constant</i>	-0.001 (-0.01)
<i>Year</i>	YES	<i>Year &amp; Firm</i>	YES
<i>N</i>	1,345	<i>N</i>	9,437
<i>Adj R<sup>2</sup></i>	0.478	<i>Adj R<sup>2</sup></i>	0.330

$$\begin{aligned}
 INV_{i,t} = & \alpha_0 + \alpha_1 BF_{i,t-1} + \alpha_2 CF_{i,t} + \alpha_3 Group_{i,t} + \alpha_4 BF_{i,t-1} * CF_{i,t} + \alpha_5 CF_{i,t} * Group_{i,t} \\
 & + \alpha_6 BF_{i,t-1} * Group_{i,t} + \alpha_7 BF_{i,t-1} * CF_{i,t} * Group_{i,t} + \delta X_{i,t} + \beta Z_{c,t} + \eta_j + \varphi_t + \varepsilon_{i,t}
 \end{aligned}
 \tag{3}$$

And the industry contract intensity ( $z_h$ ) is calculated by equation (4), following Nunn (2007) and Li and Wang (2010). In equation (4),  $\theta_{hk} = u_{hk}/u_h$ , where  $u_{hk}$  is the value of input  $k$  used in industry  $h$ , and  $u_h$  is the total value of all inputs used in industry  $h$ ;  $R_k^{neither}$  is the proportion of input  $k$  that is neither sold on an organised exchange nor reference priced;  $R_k^{reference}$  is the proportion of input  $k$  that is not sold on an organised exchange but is reference priced. A larger value of  $z_h$  indicates that industry  $h$  relies more on specific investments and is more contract intensive.

$$z_h = \sum \theta_{hk} (R_k^{neither} + R_k^{reference})
 \tag{4}$$

We expect  $\alpha_7$  to be significantly negative. In Table 6, the coefficients on  $BF*CF*MoreContract$  are significantly negative, which is consistent with our expectation.

**Table 6.** Cross-sectional tests based on corporate contract intensity.

	(1)	(2)	(3)	(4)
	<i>INV</i>	<i>INV</i>	<i>INV</i>	<i>INV</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*CF*MoreContract</i>	-0.115** (-2.09)	-0.117** (-2.06)	-0.099* (-1.84)	-0.108** (-1.96)
<i>BF*CF</i>	0.046 (1.10)	0.024 (0.58)	0.029 (0.71)	0.057 (1.36)
<i>CF*MoreContract</i>	-0.033 (-0.56)	-0.030 (-0.51)	-0.028 (-0.47)	-0.036 (-0.60)
<i>BF*MoreContract</i>	0.007 (1.31)	0.004 (0.86)	0.003 (0.71)	0.008 (1.55)
<i>MoreContract</i>	-0.069** (-2.31)	-0.070** (-2.34)	-0.069** (-2.31)	-0.069** (-2.29)
<i>BF</i>	-0.004 (-1.04)	-0.002 (-0.60)	-0.003 (-0.91)	-0.004 (-1.07)
<i>CF</i>	0.051 (1.05)	0.049 (1.01)	0.048 (1.00)	0.055 (1.11)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	4,224	4,224	4,224	4,224
<i>Adj R<sup>2</sup></i>	0.339	0.340	0.339	0.338

The industry contract intensity index is derived from Nunn (2007). Since this index is only for the manufacturing industry, the sample observations in Table 6 are less than that in the main test.

#### 4.3.2. Corporate intangible assets

In comparison with tangible assets, it is difficult to obtain information on intangible assets, leading to difficulty in asset valuation. And intangible assets also lead to soft information, thus making it more difficult for firms with more intangible assets to obtain loans from banks. However, digital transformation provides banks with high-quality technical tools for valuing intangible assets, thus making it easier for banks to process soft information. Therefore, we predict that the effect of bank digital transformation on corporate financial constraints is more pronounced for firms with more intangible assets.

To test this expectation, *Group* in model (3) is replaced by a dummy variable for firms with more intangible assets (*MoreInt*), with *MoreInt* taking the value of one when the proportion of intangible assets of the firm is in the top tecile of the sample and zero otherwise. We expect the coefficients on *BF\*CF\*MoreInt* to be significantly negative. The regression results are shown in Table 7, where the coefficients on the interaction term *BF\*CF\*MoreInt* are significantly negative, which is in line with our expectation.

#### 4.3.3. Corporate external information environment

The poorer the information environment of companies, the greater the information asymmetry between banks and companies. And bank digital transformation can help decrease information search, processing, and verification costs, thus reducing information asymmetry. Therefore, we expect that the effect of bank digital transformation on corporate financial constraints is more pronounced for firms with a poorer external information environment. To test this inference, *Group* in model (3) is replaced by the less following analysts dummy (*LessAnalyst*). Specifically, *LessAnalyst* takes the value of one when the number of following analysts is in the bottom tecile of the sample and zero otherwise. We expect  $a_7$  to be significantly negative.

**Table 7.** Cross-sectional tests based on corporate intangible assets.

	(1)	(2)	(3)	(4)
	<i>INV</i>	<i>INV</i>	<i>INV</i>	<i>INV</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*CF*MoreInt</i>	<b>-0.085**</b> <b>(-2.40)</b>	<b>-0.065*</b> <b>(-1.73)</b>	<b>-0.078**</b> <b>(-2.19)</b>	<b>-0.082**</b> <b>(-2.44)</b>
<i>BF*CF</i>	-0.010 (-0.44)	-0.019 (-0.77)	-0.013 (-0.56)	-0.003 (-0.14)
<i>CF*MoreInt</i>	-0.063* (-1.73)	-0.057 (-1.56)	-0.058 (-1.62)	-0.065* (-1.80)
<i>BF*MoreInt</i>	0.003 (1.08)	0.003 (1.17)	0.002 (0.80)	0.003 (1.07)
<i>MoreInt</i>	-0.002 (-0.56)	-0.002 (-0.70)	-0.002 (-0.65)	-0.002 (-0.53)
<i>BF</i>	0.000 (0.13)	0.001 (0.30)	0.000 (0.07)	0.000 (0.00)
<i>CF</i>	0.098*** (4.15)	0.098*** (4.13)	0.099*** (4.17)	0.098*** (4.18)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R<sup>2</sup></i>	0.331	0.331	0.331	0.331

**Table 8.** Cross-sectional tests based on corporate external information environment.

	(1)	(2)	(3)	(4)
	<i>INV</i>	<i>INV</i>	<i>INV</i>	<i>INV</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*CF*LessAnalyst</i>	<b>-0.240**</b> <b>(-2.05)</b>	<b>-0.149*</b> <b>(-1.65)</b>	<b>-0.154*</b> <b>(-1.82)</b>	<b>-0.324**</b> <b>(-2.07)</b>
<i>BF*CF</i>	-0.032* (-1.75)	-0.035* (-1.79)	-0.031 (-1.63)	-0.026 (-1.53)
<i>CF*LessAnalyst</i>	-0.121* (-1.84)	-0.089 (-1.34)	-0.066 (-0.99)	-0.174** (-2.36)
<i>BF*LessAnalyst</i>	0.004 (0.60)	0.002 (0.42)	0.001 (0.27)	0.006 (0.76)
<i>LessAnalyst</i>	-0.017*** (-3.32)	-0.018*** (-3.74)	-0.018*** (-3.75)	-0.016*** (-2.80)
<i>BF</i>	0.001 (0.56)	0.001 (0.81)	0.001 (0.30)	0.001 (0.51)
<i>CF</i>	0.082*** (4.12)	0.084*** (4.17)	0.084*** (4.15)	0.082*** (4.13)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R<sup>2</sup></i>	0.334	0.334	0.334	0.334

The results of Table 8 show that the coefficients on the interaction term *BF\*CF\*LessAnalyst* are significantly negative, which is in line with our expectation.

#### 4.4. Mechanism tests

We further explore the channels through which bank digital transformation alleviates corporate financial constraints. We perform the tests based on the size of debt financing

and use the following two variables: new long-term loans ( $\Delta LTLOAN$ ), measured as the change in long-term loans scaled by total assets; and new short-term loans ( $\Delta STLOAN$ ), measured as the change in short-term loans scaled by total assets. We also perform the tests based on the cost of debt (*Cost of debt*), measured as the interest expense scaled by lagged liabilities.

The impact of bank digital transformation on firms' long-term and short-term loans is shown in Panel A and B of Table 9. The results in Panel A show that the coefficients on *BF* are significantly positive (except for column (3)), indicating that bank digital transforma-

**Table 9.** Mechanism tests.

Panel A: New long-term loans				
	(1)	(2)	(3)	(4)
	$\Delta LTLOAN$	$\Delta LTLOAN$	$\Delta LTLOAN$	$\Delta LTLOAN$
	<i>BF</i> = <i>BankTech</i>	<i>BF</i> = <i>BankOrg</i>	<i>BF</i> = <i>BankPduc</i>	<i>BF</i> = <i>BankCon</i>
<i>BF</i>	<b>0.003**</b> <b>(2.15)</b>	<b>0.002**</b> <b>(2.18)</b>	<b>0.001</b> <b>(0.90)</b>	<b>0.003**</b> <b>(2.15)</b>
<i>CF</i>	-0.074*** (-5.11)	-0.074*** (-5.10)	-0.074*** (-5.09)	-0.074*** (-5.10)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R</i> <sup>2</sup>	0.256	0.256	0.256	0.256
Panel B: New short-term loans				
	(1)	(2)	(3)	(4)
	$\Delta STLOAN$	$\Delta STLOAN$	$\Delta STLOAN$	$\Delta STLOAN$
	<i>BF</i> = <i>BankTech</i>	<i>BF</i> = <i>BankOrg</i>	<i>BF</i> = <i>BankPduc</i>	<i>BF</i> = <i>BankCon</i>
<i>BF</i>	<b>-0.001</b> <b>(-0.55)</b>	<b>-0.001</b> <b>(-1.00)</b>	<b>-0.001</b> <b>(-0.50)</b>	<b>-0.000</b> <b>(-0.27)</b>
<i>CF</i>	-0.236*** (-14.35)	-0.236*** (-14.34)	-0.236*** (-14.35)	-0.236*** (-14.35)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R</i> <sup>2</sup>	0.098	0.098	0.098	0.098
Panel C: The cost of debt financing				
	(1)	(2)	(3)	(4)
	<i>Cost of debt</i>	<i>Cost of debt</i>	<i>Cost of debt</i>	<i>Cost of debt</i>
	<i>BF</i> = <i>BankTech</i>	<i>BF</i> = <i>BankOrg</i>	<i>BF</i> = <i>BankPduc</i>	<i>BF</i> = <i>BankCon</i>
<i>BF</i>	<b>-0.000</b> <b>(-0.19)</b>	<b>-0.000</b> <b>(-0.19)</b>	<b>-0.000</b> <b>(-0.48)</b>	<b>0.000</b> <b>(0.05)</b>
<i>CF</i>	0.007 (1.18)	0.007 (1.18)	0.007 (1.18)	0.007 (1.18)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R</i> <sup>2</sup>	0.470	0.470	0.470	0.470

tion alleviates corporate financial constraints by increasing long-term loans. And the results for short-term loans in Panel B show that the coefficients on  $BF$  are not significant, indicating that bank digital transformation does not affect firms' short-term loan financing. The result may be due to the fact that banks face less information asymmetry in short-term lending compared to long-term lending, thus banks benefit more from decrease in information asymmetry resulted from bank digital transformation in long-term lending. Besides, the results in Panel C show that the coefficients on  $BF$  are not significant, that is, bank digital transformation does not affect the cost of debt. This result may be due to the fact that the cost of debt financing is determined by corporate credit risk, and bank digital transformation does not change corporate credit risk and is unlikely to affect the cost of debt.

In summary, bank digital transformation alleviates corporate financial constraints through increasing debt financing rather than lowering financing cost.

## 5. Additional analysis

### 5.1. The impact of bank digital transformation on bank market structure

As big banks have larger abilities to access, invest and apply digital resources than small banks, digital transformation may narrow the gap between big and small banks in dealing with soft information, and reduce the information disadvantages of big banks in using soft information, thus intensifying competition between big and small banks. Therefore, digital transformation of big banks may threaten the dominant role of small and medium-sized banks in the local credit market, leading to a crowding-out effect. We estimate the following model using detailed firm-year-bank loan information.

$$\begin{aligned} Loan_{i,j,t} = & \alpha_0 + \alpha_1 BF_{j,t} + \alpha_2 BigBank_j + \alpha_3 BF_{j,t} * BigBank_j + \delta X_{i,t} + \theta B_{j,t} + \beta Z_{c,t} + \eta_i + \gamma_j \\ & + \varphi_t + \varepsilon_{i,j,t} \end{aligned} \quad (5)$$

where loan size ( $Loan_{i,j,t}$ ) is the logarithm of the amount of loans obtained by firm  $i$  from bank  $j$  in year  $t$ . The independent variable  $BF_{j,t}$  is measured as the digital transformation index or sub-indices of bank  $j$  in year  $t$ . We define large state-owned commercial banks and joint-stock banks as big banks,<sup>4</sup> and  $BigBank$  is the big bank dummy variable, which takes the value of one if bank  $j$  is a big bank and zero otherwise.  $\eta_i$ ,  $\gamma_j$ , and  $\varphi_t$  are firm, bank, and year fixed effects. In addition to the control variables in model (1), we further include bank-level control variables ( $B$ ), including: total bank assets ( $BankSIZE$ ), and bank performance ( $BankROA$ ). The coefficients on  $BF*BigBank$  are expected to be significantly positive.

Column (1) of Table 10 shows that the coefficient on  $BF*BigBank$  is significantly positive at the 1% level. Columns (2)-(4) report the results for the three sub-indices, which are in line with column (1). The above results show that bank digital transformation promotes lending by big banks, creating a crowding-out effect on small banks.

<sup>4</sup>According to the balance sheets of 469 banks in 2019, the total assets of large state-owned commercial banks (6 banks) and joint-stock banks (12 banks) accounted for 75.70% of the total assets of all banks, or 52.90% and 22.80% respectively. Therefore, the above two types are identified as big banks.

**Table 10.** Effects of bank digital transformation on bank market structure.

	(1)	(2)	(3)	(4)
	<i>Loan</i>	<i>Loan</i>	<i>Loan</i>	<i>Loan</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*BigBank</i>	<b>0.055***</b> <b>(3.98)</b>	<b>0.023*</b> <b>(1.75)</b>	<b>0.043***</b> <b>(3.55)</b>	<b>0.061***</b> <b>(4.20)</b>
<i>BF</i>	-0.049*** (-3.28)	-0.028** (-2.26)	-0.010 (-0.84)	-0.054*** (-3.63)
<i>CF</i>	-0.074 (-1.19)	-0.076 (-1.22)	-0.077 (-1.22)	-0.073 (-1.17)
<i>Controls</i>	YES	YES	YES	YES
<i>Bank &amp; Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	59,212	59,212	59,212	59,212
<i>Adj R<sup>2</sup></i>	0.491	0.491	0.491	0.491

The bank fixed effects absorb the effect of *BigBank*, so the coefficients on *BigBank* are not reported.

## 5.2. The impact of the “Internet Finance” policy

The People’s Bank of China and other relevant government departments directly promulgated the ‘Guiding Opinion on Promoting the Healthy Development of Internet Finance’ in July 2015. This document aimed to guide the compliant and sustainable development of Internet finance and encourage banks and other financial institutions to rely on Internet technologies to transform and upgrade their traditional financial businesses and services.

Banks with a high development of digital transformation have already invested in certain hardware and software, and their employees have corresponding skills to adapt to digital transformation. Thus, the ‘Internet Finance’ policy can quickly help them to transform and upgrade their business. However, it is difficult for banks with a low development of digital transformation to discard the knowledge and capabilities built on the traditional lending decisions and quickly adapt or transition to the new digital system. Therefore, it usually takes more time for the ‘Internet Finance’ policy to take into effect for banks with a low development of digital transformation. As a result, we expect the effect of the ‘Internet Finance’ policy to be stronger for banks with a high development of digital transformation than banks with a low development of digital transformation.

Then, we distinguish two groups with a high or low development of bank digital transformation based on their bank digital transformation index in 2014 (one year before the implementation of ‘Internet Finance’ policy), and further compare the changes in corporate financial constraints between the two groups before and after the implementation of the policy. We estimate the following model:

$$\begin{aligned}
 INV_{i,t} = & \alpha_0 + \alpha_1 Post_t + \alpha_2 HighBF_i + \alpha_3 CF_{i,t} + \alpha_4 Post_t * CF_{i,t} + \alpha_5 HighBF_i * CF_{i,t} + \alpha_6 Post_t \\
 & * HighBF_i + \alpha_7 Post_t * HighBF_i * CF_{i,t} + \delta X_{i,t} + \beta Z_{c,t} + \eta_i + \varphi_t + \varepsilon_{i,t}
 \end{aligned}
 \tag{6}$$

where *Post* is the ‘Internet Finance’ policy dummy variable, which takes the value of one in 2015 and beyond, and zero otherwise. *HighBF* is a dummy variable equal to one for sample observations with a high development of bank digital transformation, which takes the value of one if the bank digital transformation index in 2014 is in the top tercile of sample distribution, and zero otherwise. We also include firm fixed effects ( $\eta_i$ ) and year fixed effects ( $\varphi_t$ ). We expect the coefficient on *Post\*HighBF\*CF* to be significantly negative.

**Table 11.** The impact of 'Internet Finance' policy.

	(1)		(2)
	<i>INV</i>		<i>INV</i>
<i>Post*HighBF*CF</i>	-0.128** (-2.01)	<i>Yr2013_2014*HighBF*CF</i>	-0.127 (-1.50)
<i>Post*CF</i>	0.079 (1.60)	<i>Yr2015*HighBF*CF</i>	-0.245* (-1.80)
<i>Post*HighBF</i>	0.004 (0.90)	<i>Yr2016*HighBF*CF</i>	-0.366** (-2.45)
<i>HighBF*CF</i>	0.010 (0.24)	<i>Aft2017*HighBF*CF</i>	-0.138 (-1.43)
<i>CF</i>	0.059* (1.92)	<i>Yr2013_2014*CF</i>	0.086 (1.24)
<i>SOE</i>	-0.002 (-0.31)	<i>Yr2015*CF</i>	0.185* (1.73)
<i>SIZE</i>	0.009** (2.57)	<i>Yr2016*CF</i>	0.177 (1.47)
<i>LEV</i>	0.027 (1.48)	<i>Aft2017*CF</i>	0.104 (1.30)
<i>TobinQ</i>	0.003** (2.26)	<i>Yr2013_2014*HighBF</i>	0.011 (1.50)
<i>OPROA</i>	0.076*** (2.90)	<i>Yr2015*HighBF</i>	0.012 (1.22)
<i>PPE</i>	-0.088*** (-4.07)	<i>Yr2016*HighBF</i>	0.016 (1.40)
<i>FIRST</i>	0.014 (0.50)	<i>Aft2017*HighBF</i>	0.011 (1.35)
<i>INDP</i>	-0.050 (-1.57)	<i>HighBF*CF</i>	0.101 (1.32)
<i>MktIndex</i>	0.006 (1.50)	<i>CF</i>	-0.004 (-0.07)
<i>GDPG</i>	-0.000 (-0.02)		
<i>GDPPER</i>	0.014 (1.07)		
<i>Constant</i>	-0.242 (-1.62)	<i>Constant</i>	-0.227 (-1.50)
<i>Year &amp; Firm</i>	YES	<i>Year &amp; Firm &amp; Controls</i>	YES
<i>N</i>	5,041	<i>N</i>	5,041
<i>Adj R<sup>2</sup></i>	0.336	<i>Adj R<sup>2</sup></i>	0.337

(1) The firm fixed effects absorb the effect of *HighBF*, while the year fixed effects absorb the effect of *Post*. Therefore, the coefficients on *HighBF* and *Post* are not reported. (2) In order to distinguish the treatment and control group, we only retain the observations with bank digital transformation data in 2014, so the sample observations in Table 11 are less than that in the main test.

Column (1) of Table 11 shows that the coefficient on *Post\*HighBF\*CF* is significantly negative, indicating that the 'Internet Finance' policy has a negative impact on the investment-cash flow sensitivity for firms with a high development of bank digital transformation.

We further test the dynamic impact of the 'Internet Finance' policy. Specifically, using year 2011–2012 as the baseline period, the indicator variable *Yr2013\_2014* is the year 2013–2014; the indicator variable *Yr2015* (or *Yr2016*) is the year 2015 (or 2016); the indicator variable *Aft2017* takes the value of one when the sample year is 2017 and beyond. Then, *HighBF* and *HighBF\*CF* are interacted with separate indicator variables for each year around the implementation of the policy. The results in column (2) of Table 11 shows that the coefficient on *Yr2013\_2014\*HighBF\*CF* is insignificant, indicating that there

**Table 12.** Economic consequences of bank digital transformation.

	(1)	(2)	(3)	(4)
	<i>INV</i>	<i>INV</i>	<i>INV</i>	<i>INV</i>
	<i>BF = BankTech</i>	<i>BF = BankOrg</i>	<i>BF = BankPduc</i>	<i>BF = BankCon</i>
<i>BF*CF*Zombie</i>	<b>0.144**</b> <b>(2.42)</b>	<b>0.135**</b> <b>(2.15)</b>	<b>0.125**</b> <b>(2.01)</b>	<b>0.132**</b> <b>(2.28)</b>
<i>BF*CF</i>	-0.072*** (-3.95)	-0.071*** (-3.54)	-0.065*** (-3.56)	-0.062*** (-3.71)
<i>CF*Zombie</i>	0.039 (0.64)	0.024 (0.39)	0.030 (0.49)	0.044 (0.72)
<i>BF*Zombie</i>	-0.011*** (-3.29)	-0.008** (-2.26)	-0.007** (-2.32)	-0.011*** (-3.57)
<i>Zombie</i>	-0.012*** (-3.08)	-0.011*** (-2.81)	-0.012*** (-2.94)	-0.013*** (-3.11)
<i>BF</i>	0.004** (2.50)	0.004** (2.41)	0.003* (1.69)	0.004** (2.46)
<i>CF</i>	0.067*** (3.37)	0.072*** (3.57)	0.072*** (3.57)	0.066*** (3.32)
<i>Controls</i>	YES	YES	YES	YES
<i>Year &amp; Firm</i>	YES	YES	YES	YES
<i>N</i>	9,437	9,437	9,437	9,437
<i>Adj R<sup>2</sup></i>	0.333	0.333	0.333	0.332

is no significant difference in corporate financial constraints between the two groups before the implementation of the 'Internet Finance' policy. However, the coefficients on *Yr2015\*HighBF\*CF* and *Yr2016\*HighBF\*CF* are both significantly negative, indicating that the 'Internet Finance' policy has a stronger impact for firms with a higher development of bank digital transformation.

### 5.3. Economic consequences of bank digital transformation

In order to investigate the economic consequences of bank digital transformation in improving credit allocation efficiency, we explore whether bank digital transformation leads to a shift in credit resources towards efficient companies.

We follow Li et al. (2020) and Liu et al. (2019) to define high-efficiency firms based on zombie firms. Specifically, we follow Huang and Chen (2017) to identify zombie firms (*Zombie*) by the real profit method and identify zombie firms as inefficient companies. Then, we examine whether bank digital transformation is more likely to alleviate the financial constraints of non-zombie firms. The regression results are shown in Table 12.

Table 12 shows that the coefficients on *BF\*CF\*Zombie* are significantly positive at the 5% level, indicating that the alleviation of corporate financial constraints by bank digital transformation is mainly in non-zombie firms. In summary, the results in Table 12 show that bank digital transformation significantly alleviates the financial constraints of high-efficiency firms and improves the efficiency of credit resource allocation.

## 6. Conclusion

In this paper we investigate the effect and economic consequences of bank digital transformation on corporate financial constraints. We find that bank digital transformation helps to alleviate corporate financial constraints, and this effect is mainly in

companies with higher contract intensity, more intangible assets, and poorer external information environment. Mechanistic tests find that bank digital transformation alleviates corporate financial constraints by increasing debt financing rather than lowering financing cost. Further, bank digital transformation promotes lending by big banks and crowds out lending by small banks. Finally, we show that bank digital transformation leads to a shift in credit resources towards high-efficiency firms, improving the efficiency of credit allocation.

Our findings also have important practical implications. First, we provide new clues for promoting financial supply-side reform. The Chinese banking system suffers from resource mismatch, such as banks selecting borrowers based on the collateral, resulting in financial exclusion of small and growth firms. We explore the mechanisms by which bank digital development affects the access of companies to credit, which sheds light on how to ease financing woes of small and medium-sized firms in China and promote financial supply-side reform.

Second, our findings have important policy implications for improving the efficiency of credit resource allocation to promote high-quality economic development of the Chinese economy. In the current period, there still exist misallocation of credit resources in China, with a large amount of credit funds flowing into inefficient firms such as zombie firms, creating a great obstacle to high-quality development. We find that bank digital transformation drives credit resources to non-zombie firms, suggesting that bank digital transformation helps alleviate misallocation of credit resources in China. Therefore, the government departments in China should pay attention to bank FinTech and encourage integration of technology with finance and capital markets, so as to better promote high-quality economic development.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This paper has the support of the Key Projects of the National Social Science Fund (22AGL013, 23AGL014), the National Natural Science Fund of China (71702192, 72132002), the Social Science Fund of Guangdong Province (GD23YGL35), Innovation and Talent Base for Income Distribution and Public Finance (B20084) and Innovation and Talent Base for Digital Technology and Finance (B21038), and Institute for Enterprise Development (Jinan University, Guangdong Province, No. 22JNZS03).

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