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Curbing credit corruption in China: The role of FinTech

Fan Su*, Chao Xu

School of Finance, Hubei University of Economics, Wuhan, Hubei 430073, China

A R T I C L E I N F O

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A B S T R A C T

FinTech is an emerging financial innovation model that promotes a "technological anti-corruption" effect. Credit corruption is a worldwide problem; however, previous studies have not focused on the anti-corruption effect of FinTech. This study first uses micro data from FinTech companies to construct city-level FinTech measurement indicators in China. An objective measurement of credit corruption is then formed by separating the expenditures for credit corruption from total business entertainment expenses. This study empirically explores the impact of FinTech on credit corruption using a sample of Chinese listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2019. The results show that FinTech can significantly curb credit corruption, and that the expenditures for credit corruption of local companies are lower with better regional FinTech. These findings are valid after addressing endogeneity issues and conducting a series of robustness tests. The results of the heterogeneity test show that FinTech offers greater advantages for risk identification, information mining, and inclusive development than traditional finance. The curbing effect on credit corruption is stronger in companies with better intrinsic quality, more transparent information disclosure, located in less financially developed and more corrupt regions. Economic consequence analysis suggests that FinTech can correct resource misallocation caused by credit corruption and promote corporate investment efficiency. These findings are valuable for policy practices for technological anti-corruption in the financial sector.

Introduction

Credit corruption is the use of financial or power resources at the bank manager's disposal, in collusion with borrowing companies, to lend money illegally in pursuit of personal gain (Fried & Howitt, 1980). Orderly and healthy development of the credit market can transform savings into investments and improve the allocation of capital efficiency (Beck et al., 2000; Greenwood & Jovanovic, 1990). However, if the credit market is eroded by corruption, the impact can be devastating. Economists warn that corruption reduces investment incentives, increases transaction costs, and reduces economic growth (Seligson, 2002). Credit corruption distorts market-oriented allocation mechanisms (Fungáčová et al., 2015). Once the benefits exchange model of "corruption in exchange for loans" floods the market, companies that pay rent to engage in credit corruption are probably approved for loans (Laeven, 2001). However, high-quality companies with no intention of bribing bank managers face difficulties in obtaining financial support (Beck et al., 2005), resulting in inefficiency and misallocation of credit resources. Thus, credit corruption can trigger financial risk. La Porta et al. (2003) argue that companies that obtain loans through corrupt practices have higher default rates than those that obtain loans through normal channels. If such corruption spreads across the financial system, financial risks would be triggered, greatly undermining the banking system's stability (Ben Ali et al., 2020).

Anti-corruption measures in the credit market pose a global challenge. Compared with other forms of corruption, credit corruption is difficult to be prevented because of its highly specialised form. Decision-makers in the credit sector use their financial expertise, monopoly on credit resources and information advantages to disguise corrupt loans as normal loans (Udell, 1989). Moreover, some bank managers package loans as shadow banking loans through financial intermediaries (Lindgren, 2018). Even if loan defaults happen, it is difficult to distinguish between risks caused by corruption and normal business risks. Moreover, people with little or no relevant financial experience may face challenges in detecting hidden undercurrents and corruption.

Recently, emerging technologies, such as big data, blockchain, artificial intelligence, and cloud computing, have been widely applied in the financial sector. FinTech has evolved as an emerging financial innovation model. This process has an unstoppable momentum that drives profound changes in the financial industry (Goldstein et al.,

* Corresponding author.
E-mail address: sufan_hbue@163.com (F. Su).

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2019). Scholars have paid more attention to the positive functions of FinTech innovation designed to improve the quality and efficiency of financial business. Through efficient algorithms and tight security systems, FinTech can promote digital and intelligent re-engineering of business, management, and services in banks (Campanella et al., 2015). FinTech can also help banks enhance their operational efficiency (Lee et al., 2021) and improve their risk controls (Banna et al., 2021; Cheng & Qu, 2020). Scholars have also found that FinTech can enhance corporate investment efficiency (Abbasi et al., 2021), increase corporate innovation output (Tang et al., 2022), promote corporate transformation and upgrading (Chen & Zhang, 2021), ease corporate financing constraints (Chen & Yoon, 2021), and reduce corporate financial risk (Ji et al., 2022).

However, these studies only focused on FinTech empowerment in financial services and the role of FinTech innovation in supporting the real economy. Actually, FinTech also enhances the standardisation and fairness of financing rules, thereby playing a critical role in curbing corruption. In the process of reducing information asymmetries, FinTech lowers the high-standard financing threshold and eases corporate financing constraints (Chen & Yoon, 2021), enabling loan applicants to be treated equally in credit assessments, without using rent for corrupt practices. Digital and intelligent analysis systems, represented by intelligent risk control has comprehensively transformed the original business and fundamentally changed the rules of credit decision-making. Additionally, objective model algorithms have replaced subjective evaluations as the core of credit decisions (Giudici, 2018), which has hit the point of curbing credit corruption. As credit approval becomes more open, transparency will be enhanced and credit corruption will be greatly reduced.

China is chosen as a case study because it is an ideal nation for studying the relationship between FinTech and credit corruption. Fig. 1 shows the total registered number and capital of China's new FinTech companies from 2011 to 2019. From 2011–2015, China's FinTech companies showed a rapid development trend, with the average annual growth rate of the registered number and capital of new companies of 81% and 117%, respectively. The growth trend peaked in 2015. However, the registered number and capital showed a downward trend since 2016. On average, 203 new companies and 33.4 billion new registered capital are recorded annually, revealing that China's FinTech development is still in a good stage. According to IResearch (2019), China accounted for approximately 3.1% of global FinTech company funding in 2014 and increased to 16.4% in 2018, with growth rates far exceeding those of Europe, the US, and other regions. Ernst and Young (2020) revealed that China's FinTech adoption rate was 87% higher than the global average (64%) during the same period.

China is a global leader in FinTech innovation, FinTech capital investment, and FinTech application scenarios. Nevertheless, the nation is afflicted with widespread corruption. The Global Corruption Perception Index 2020 ranked China 78th out of 180 most corrupted countries. China's position regarding the corruption rate does not match its economic strength. Since the 18th National Congress of the Communist Party of China was adopted, anti-corruption measures in the financial sector have become the focus (Li & Chan, 2021). In 2019, over 6900 illegal cases in the financial sector were investigated, and the culprits were prosecuted. Most culprits were bank executives who used credit approval powers to derive personal gains. Such a high number of corruption cases show that corruption in China's credit market can no longer be ignored and should be curtailed to prevent the spread of financial risks. With the rate of FinTech growth, the current credit corruption in China is a good example for investigating how FinTech affects credit corruption.

This study focuses on the impact of FinTech on credit corruption. We use microdata of FinTech companies in China to construct city-level FinTech measurement indicators and separate the expenditures for credit corruption from companies' business entertainment expenses to construct the measurement of credit corruption. The empirical results of a sample of Chinese listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2019 show that FinTech can significantly curb credit corruption. It is indicated that the expenditures for credit corruption of local companies are lower if regional FinTech is better managed and records high development. The heterogeneity tests find that FinTech has a stronger curbing effect on credit corruption in companies with better intrinsic quality, more transparent information disclosure, and located in less financially developed and more corrupt regions. Finally, because credit corruption causes efficiency losses in resource allocation, we explore whether FinTech can mitigate the adverse economic consequences of credit corruption. The tests show that FinTech can effectively correct resource misallocation and promote efficiency of credit allocation.

We may make contributions in the following aspects: First, many studies have discussed the impacts of FinTech on financial markets

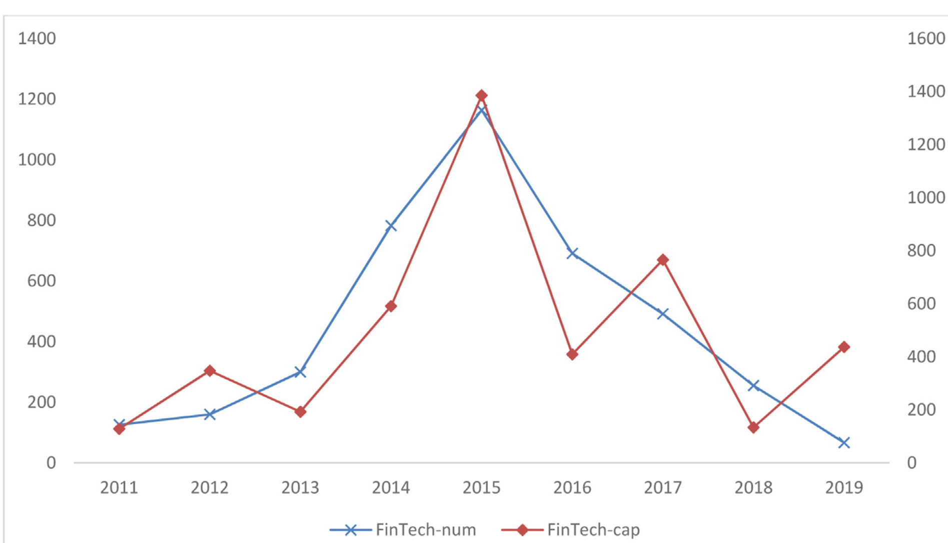

Fig. 1. Line graph of registered number and capital of new China's FinTech companies from 2011 to 2019
Note: Data are collected from the CSMAR database. The left Y-axis represents the registered number of new FinTech companies in China, and the right Y-axis represents the registered capital of new FinTech companies in China. The units on the right Y-axis are 100 million CNY.

and the real economy from the viewpoint of financing outcomes (Campanella et al., 2015; Tang et al., 2022). However, little attention has been paid to the financing processes and rules of the FinTech model, especially their impact on credit corruption. We identify the curbing effect of FinTech on credit corruption from the new perspective of "technological anti-corruption." Second, most existing studies use questionnaire surveys to measure credit corruption (Akins et al., 2017; Barth et al., 2009). This method limits the scope of the sample to a specific year and the empirical data are mostly cross-sectional. Moreover, the authenticity of the survey data has been questioned because most companies tend to cover authentic information (Chan et al., 2020). Following measure using business entertainment expenses (Cai et al., 2011; Chan et al., 2020), this study separates the expenditures for credit corruption from the total business entertainment expenses to form an objective measurement of credit corruption applicable to panel data. Finally, through an extended analysis, we identify FinTech's applicable environment to curb credit corruption and find its advantages in risk identification, information mining, and inclusive development. With an economic consequence analysis, we prove the application value of anti-corruption using FinTech in correcting resource misallocation and promoting corporate investment efficiency.

The rest of this paper is structured as follows. Section 2 presents the theoretical analysis and develops the research hypotheses. Section 3 focuses on the research design, which includes research variables, models, and samples. Section 4 presents the empirical results, including benchmark regression, endogeneity issues, robustness tests, heterogeneity analysis, and economic consequence analysis. Finally, Section 5 summarises the conclusions and policy recommendations.

Theoretical analysis and research hypotheses

Credit corruption has become a popular topic among academics and policymakers. Studies have argued that credit corruption is a "lubricant" for economic operation, which helps bypass red tape and speed up loan approval (Li et al., 2008; Zeume, 2017). However, other studies believe that credit corruption is a "stumbling block" that can distort market-oriented allocation in the long term (Fungáčová et al., 2015), which reduces the likelihood of high-quality companies obtaining loans (Beck et al., 2005). Credit corruption can also trigger credit risk under certain conditions (Ben Ali et al., 2020). Given the potentially significant damage caused by credit corruption, governments globally are taking various measures to combat credit corruption.

Stricter financial regulations (Beck et al., 2006), higher quality disclosure (Barth et al., 2009), stronger interbank competition (Sharma & Paramati, 2021), and better internal governance (Nguyen et al., 2019) have been implemented to curb credit corruption. However, in the traditional financial model, these measures have failed to change the centrality of bank credit management and fundamentally address the principal-agent problem between bank owners and managers. With the current level of corruption globally, both developed and emerging countries are plagued by credit corruption (Park, 2012). China's financial market is among the largest in the world. By the end of 2019, China's RMB credit balance had exceeded $150 trillion, ranking first worldwide. China's stock market has a market capitalization of over $60 trillion and a bond market custody balance of nearly $100 trillion, ranking second globally. However, institutional problems, such as weak internal governance, serious information asymmetries, inadequate market competition, and excessive reliance on collateral, have led to widespread credit corruption. Although an unprecedented financial anti-corruption campaign was launched in the wake of the 18th Party Congress (Li & Chan, 2021), correcting these inherent disadvantages in the economic system and fighting against credit corruption in China remain significant challenges.

Apart from traditional methods, such as administrative reform and legal construction, the application of technological innovation to control and prevent corruption has received increasing attention worldwide. Scholars have found that emerging information technologies are important tools for building an incorruptible government. Emerging information technologies can generate rigid procedural controls, compress the discretionary powers of administrative officials, improve the transparency of government decision-making procedures, and increase the effectiveness of internal and external organizational oversight (Srivastava et al., 2016). Theoretically, FinTech is a high-level integration of finance and technology that has the general characteristics of technology application, and the effect of "technological anti-corruption" is expected to exist in the credit market as well.

Information asymmetry, overreliance on collateral, and financing discrimination are prominent in the Chinese financial system, causing many companies to face financing constraints (Chen & Yoon, 2021). Thus, companies in weak positions are forced to engage in corrupt practices to compete for limited credit resources. FinTech is a cutting-edge technological innovation developed to reduce information asymmetry in financial markets, broaden the boundaries of financial business, and allow companies to have access to credit (Sheng, 2021). This cutting-edge IT tool assists banks in acquiring and processing information effectively. Outside the traditional credit information system, FinTech can mine large amounts of unstructured data, including real-time point-of-sale transaction data (Zhu, 2019), social media data (Jagtiani & Lemieux, 2019), user review data (Frost et al., 2019) and satellite imagery data (Zhu, 2019). FinTech also improves analytical capabilities and assists in efficiently processing banking information. Using technological innovation, collected soft information is transformed into valuable hard information for efficient credit evaluation (Gambacorta et al., 2020). This mode of operation reduces the information asymmetry problem and breaks the original "glass door" in the credit market. To sum up, FinTech facilitates financial inclusiveness, alleviates corporate finance constraints, and reduces credit corruption on the demand side of companies.

Although traditional credit businesses apply risk-control models, the entire approach is dominated by subjective decisions and supplemented by objective models. As long as bank managers continue to hold the core power of credit approval, credit corruption will be of greater interest. FinTech has transformed traditional credit risk control into an intelligent one, thereby profoundly changing the rules of credit decision-making. With the help of intelligent risk control, banks can significantly reduce operational costs, lower subjective decision-making errors, and improve the standardisation of credit decision making (Giudici, 2018).

Regarding FinTech application, the starting point is to review and screen companies more efficiently (Cheng & Qu, 2020) to improve credit business practices. However, the relative importance of subjective and model decisions has been unintentionally altered, as credit decisions are driven by programmed and intelligent modelling systems instead of managers' subjective judgments (Ashta & Herrmann, 2021). This innovation greatly reduces the phenomenon of black-box operations, reduces the abuse of power for personal gain, and compresses managers' ability to demand bribes. Once the objective standards for credit decisions reach a market consensus, they contain the governance effect on companies (Zhu, 2019). Companies can obtain a fair risk assessment by following the normal application process without establishing a beneficial relationship with bank managers. After all, paying corruption rents does not change the objective of scoring the risk control model. Thus, innovation in financing rules based on FinTech applications is key to tackling credit corruption, which has been an important anti-corruption breakthrough in the credit market.

FinTech facilitates transparency and openness in process management. By improving the application of IT tools, FinTech enhances banks' internal control systems, and creates a continuous and high-intensity deterrent to corruption. A digital and intelligent internal control system can monitor all aspects of a bank's credit operations 24/7, identify abnormalities, and prevent corruption. Importantly, the internal control system built by FinTech is self-learning; it can be updated with new features of corruption and can effectively strengthen internal control to facilitate the anti-corruption in credit market. FinTech also enhances the implementation of effective regulatory technologies (Kavassalis et al., 2018). The data used by banks' internal control systems are bounded; financial regulators can expand the data sources to strengthen anti-corruption policies with the help of regulatory technology. Moreover, data from multiple sectors, such as financial accounts, real estate, industry and commerce, taxation, and consumption records, can be used to conduct all-around and dead-end supervision of credit operations to form a stronger deterrent to credit corruption.

Based on the above analysis, this paper puts forward the following hypothesis:

Hypothesis 1. FinTech can curb credit corruption.

FinTech is not policy-based finance, and the credit availability it creates does not cover all companies. With the application of new FinTech tools, banks can develop more accurate risk assessment systems and rigorously screen companies (Banna et al., 2021) to allocate funds to high-quality companies. Under the FinTech credit model, the intrinsic quality of a company plays a critical role in credit decisions. Companies with high profitability and low risk in financing will naturally be given higher priority based on the outcomes of transparency and intelligent processes. Even if these companies do not pay rent to credit decision-makers, they still have a high probability of obtaining credit funds. FinTech will not ease its financing constraints for less-profitable and riskier companies. Therefore, there is still room to engage in credit corruption for these low-quality companies, either actively or passively. Based on the heterogeneity of intrinsic quality, this study proposes the following hypothesis.

Hypothesis 2. The curbing effect of FinTech on credit corruption is stronger in companies with better intrinsic quality.

Information is vital to FinTech effectiveness. Transparent information disclosure can provide high-quality data resources for the FinTech credit model and create better technological synergy for innovation (Frost et al., 2019). Companies with high-quality disclosure have a higher level of information transparency, which contributes to a clearer and more objective assessment of the FinTech credit model. For companies with low information transparency, there is more room for subjective judgment in the assessment results, creating room for corrupt activities. Based on the heterogeneity of information disclosure, this study proposes the following hypothesis.

Hypothesis 3. The curbing effect of FinTech on credit corruption is stronger in companies with more transparent information disclosure.

China is a vast country characterised by unbalanced regional development. In less financially developed regions, financial repression and various institutional factors constrain the efficiency of financial resource allocation, leading to a high incidence of corruption in the credit sector. However, such an environment provides room for FinTech applications. In less financially developed regions, FinTech can break down existing financial repression and promote the standardisation and transparency of credit processes, which have a greater marginal effect on curbing credit corruption. In more corrupt regions, FinTech application can alleviate the shortcomings of the credit approval process, block the breeding channel of corruption, and produce a stronger anti-corruption effect. Based on the heterogeneity of regional differences, this study proposes the following hypothesis.

Hypothesis 4. The curbing effect of FinTech on credit corruption is stronger in less financially developed and more corrupt regions.

The framework diagram of FinTech's theoretical mechanism on credit corruption is shown in Fig. 2.

Research design

Variables

Explained variable: credit corruption.

Credit corruption is defined as the use of credit decision-making power at bank managers' disposal to illegally lend money. However, measuring this type of corruption is challenging. The existing literature has developed two main approaches to measuring general corruption from the corporate expenditure perspective. The first approach involves obtaining direct information about a company's corrupt practices through a questionnaire survey (Akins et al., 2017; Barth et al., 2009). The second is to indirectly reflect corrupt corporate practices based on anomalies in financial statements, using business entertainment expenses to measure corporate corruption expenditure (Cai et al., 2011; Chan et al., 2020). However, the questionnaire survey is expensive to implement, and the data collected are limited to a specific year and cannot be matched to continuous

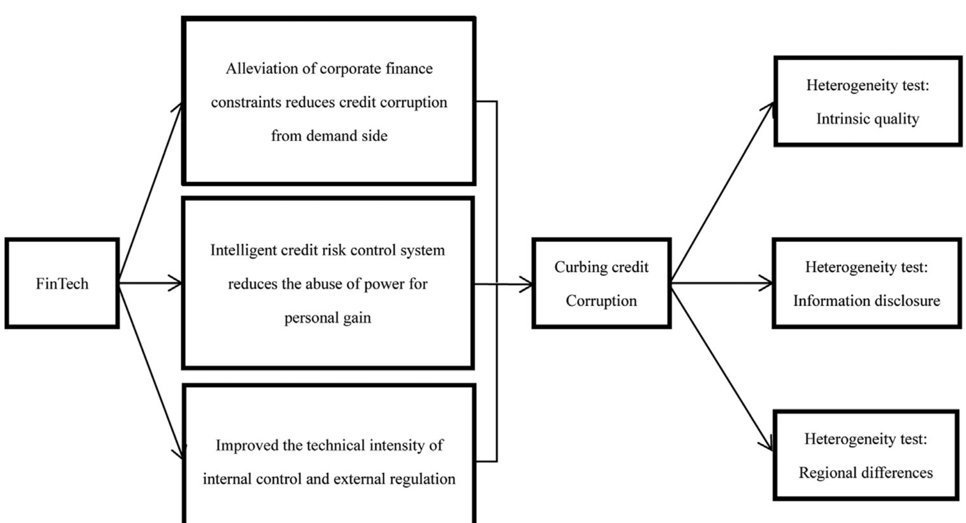

Fig. 2. Framework diagram of theoretical analysis.

observations of FinTech development. Thus, this study measures credit corruption using anomalies in financial statements. Business entertainment expenses and excess management fees are the two most common vehicles for capturing general corporate corruption. Since a broad category of management fees covers various corporate payments and its anomalous component is noisier, this study chooses business entertainment expenses related to corrupt expenditure to construct an indicator of credit corruption.

Corporate credit corruption is the explained variable, which reveals that we cannot use standardised business entertainment expenses as a proxy variable, and must remove the interference of factors such as daily operations and other matters. Following Dechow et al. (1995), we construct a regression model as follows:

$$Fee_{i,t} = \alpha_0 + \alpha_1 Lnsale_{i,t} + \alpha_2 Growth_{i,t} + \alpha_3 Big4_{i,t} + \alpha_4 Hhi_{i,t} + \alpha_5 Manager_{i,t} + Year + Ind + \varepsilon_{i,t} \quad (1)$$

In model (1), *Fee* is the proportion of business entertainment expenses to total management expenses; *Lnsale* is the natural logarithm of operating revenue; *Growth* is the operating income growth rate; *Big4* is whether the auditing institution is the Big Four accounting firm, and *Big4* = 1 if it is Big Four, otherwise *Big4* = 0; *Hhi* is the sum of the squares of the top five major company shareholders; *Manager* is the natural logarithm of the number of executives; *Year* and *Ind* are the year and industry dummy variables, respectively; $\varepsilon_{i,t}$ is the residual term. The fitted value *Feef* for the business entertainment expenses ratio (*Fee*) is obtained by estimating Model (1). The actual value (*Fee*) minus the fitted value (*Feef*) is the adjusted business entertainment expense ratio indicator (*AdjFee*).

Although Model (1) filters out the effects of some factors, the adjusted business entertainment expense ratio (*AdjFee*) does not exhibit an idiosyncratic nature applied to credit resources. Our differentiation strategy is to use companies that have not obtained new loans as a reference sample and calculate their inner-group mean of *AdjFee,* labelled as *MFee* by industry and year. We assume that only companies that obtain loans may pay corruption rents; thus, the *MFee* of companies that have not obtained new loans can be used as a benchmark for no credit corruption. Logically, after adjusting for individual effect, industry effect, and year effect, credit corruption is due to the excess of *AdjFee* for companies with new loans compared with firms without loans. For companies to obtain new loans in a year, the difference between *AdjFee* and *MFee* is a proxy variable for credit corruption. We set the credit corruption variable *Rent* = *AdjFee* − *MFee* if *AdjFee* ≥ *MFee*, and set *Rent* = 0 if *AdjFee* < *MFee*.

(i) Explanatory variables: FinTech.

Three major approaches were used to measure FinTech development. First, web crawler technology was used to extract FinTech keywords and synthesise FinTech measurement based on the search volume (Cheng & Qu, 2020). Second, the Digital Financial Inclusion Index compiled by the Digital Finance Research Centre of Peking University was used to represent the regional FinTech development (Ye et al., 2022). Third, a measurement indication was constructed to reflect the activity of FinTech development based on regional FinTech companies' data (Lee et al., 2021; Zhao et al., 2022). With web crawlers, it is difficult to cover the overall FinTech information because of the limited content of news media reports and the direct summation of word frequency numbers that ignore the differences in information. The Digital Inclusive Finance Index, derived from the small and micro businesses data served by Ant Financial Services (Alipay), does not logically match the sample of listed companies.

This study chooses the microdata of FinTech companies to construct FinTech measurement indicators, owing to their better consistency, coherence, and comparability. This method eliminates problems associated with inconsistent indicator specifications using the web crawler method. Simultaneously, FinTech companies are critical for promoting FinTech business, whose activities are highly correlated with FinTech development in a city. This process helps to evaluate FinTech in terms of measurement content. FinTech companies' data are gathered from the FinTech Company Information Module in the CSMAR database, which stores information about FinTech registrations, investments, and financing. We collect data associated with the registered capital and financing events of FinTech companies at the city level, from which these three indicators are constructed:

(1) Number of FinTech companies *Ftn*, expressed as *Ftn* = Ln (sum of surviving FinTech companies + 1);

(2) Capital of FinTech companies *Ftv*, expressed as *Ftv* = sum of registered capital of surviving FinTech companies / urban per capita GDP; and

(3) Financing frequency of FinTech companies *Ftf*, expressed as *Ftf* = Ln (sum of the frequency of financing events for FinTech companies + 1).

These three FinTech indicators are characterised by common drivers and unique information. Using only one indicator results in estimation bias. Therefore, this study chooses principal component analysis to reduce data dimensionality and construct a comprehensive FinTech measurement indicator. Thus, we conducted Kaiser-Meyer-Olkin (KMO) and Bartlett tests on the initial variables, and the results indicated a strong correlation between the three FinTech variables, which met the prerequisites for principal component analysis. According to the Kaiser-Harris criterion, we retain the first principal component, whose eigenvalue is greater than 1, as the comprehensive measurement indicator of FinTech *Ft.* The variance contribution of the first principal component is 89.80%, which explains that the information in the initial variables is well represented. Finally, we normalise the FinTech measurement indicators (*Ft* and each sub-indicator *Ftn, Ftv,* and *Ftf*) and divide them by 100 (the interval is 0 to 0.01) to display the estimation coefficient.

(iii) Control variables.

Following Barth et al. (2009), we introduce the main company-level control variables as *Lev* (leverage ratio), *Size* (corporate size), *Growth* (corporate growth), *Roa* (return on total assets), *Tang* (asset structure), *Nature* (nature of ownership), *Top1* (shareholding ratio of the largest shareholder), *Direct* (ratio of independent directors), *Cflow* (Cash flow), and *Salary* (salary). The definitions of these variables are listed in Table 1.

Model setting

The benchmark model for the impact of FinTech on credit corruption is set as follows:

$$Rent_{i,t} = \alpha + \beta Ft_{j,t-1} + \gamma Controls + Year + Ind + \varepsilon_{i,t} \quad (2)$$

In Model (2), *i* denotes the company, *j* denotes the city in which the company is located, and *t* denotes the year. The explained variable *Rent* is credit corruption and the explanatory variable is the comprehensive measurement indication of FinTech *Ft* obtained using principal component analysis. *Controls* are a set of control variables that may affect credit corruption. To reduce the omitted variable bias, the model also controls for the year effect *Year* and industry effect

Table 1

Variables	Definition
Rent	Credit corruption, as detailed in the previous section on variable definitions.
Ft	A comprehensive measurement indication of FinTech obtained using principal component analysis, as detailed in the variable definitions section above.
Ftn	Number of FinTech companies, a sum of the number of surviving FinTech companies plus 1, and taken its natural logarithm.
Ftv	Capital of FinTech companies, a sum of registered capital of surviving FinTech companies divided by city GDP per capita.
Ftf	Frequency of financing events for FinTech companies, the sum of the frequency of financing events for FinTech companies plus 1, and taken its natural logarithm.
Lev	Leverage ratio, the ratio of total liabilities to total assets.
Size	Corporate size, the natural logarithm of total assets.
Growth	Corporate growth, operating income growth rate
Roa	Return on total assets, the ratio of net profit to total assets
Tang	Asset structure, the ratio of fixed assets and inventories to total assets
Nature	Nature of ownership, equal 1 if the company is a state-owned company, otherwise equal 0
Top1	Shareholding ratio of the largest shareholder, the ratio of the shares held by the largest shareholder to the total share capital
Direct	Ratio of independent directors, the ratio of the number of independent directors to the total number of board directors
Cflow	Cash flow, the ratio of net cash flow from operating activities to total assets
Salary	Executive salary, the natural logarithm of the average executive salary

Ind. $\varepsilon_{i,t}$ denotes the residual term. To mitigate inverse causality, a first-order lagged term is used for FinTech variable *Ft* and the control variables. To mitigate autocorrelation and heteroskedasticity, the model estimation uses robust standard errors clustered by industry.

Data sources and descriptive statistics

Our research sample consists of companies listed on the Shanghai and Shenzhen stock exchanges in China from 2011 to 2019. The company registration data used to construct the FinTech indicators are collected from the FinTech company information module in the CSMAR database. The Digital Inclusive Finance Index, used for robustness testing is sourced from the Third Edition of the Digital Inclusive Finance Index published in 2021. Data on business entertainment expenses used to construct the credit corruption variable are sourced from the CNRDS database. All other relevant company data are from the CSMAR database, and city-level relevant data are sourced from the China City Statistical Yearbook.

The original sample is adjusted as follows: (1) excluding financial companies, (2) excluding companies treated as ST, ST*, and PT during the sample period, (3) excluding the missing observation values of corporate business entertainment expenses, (4) retaining only those companies with continuous observations for more than five years, and (5) truncating all continuity variables by 1%. After screening, 10, 631 observations were obtained.

Table 2 presents the descriptive statistics of the variables. The mean of the credit corruption variable *Rent* is 0.009, indicating that a company will spend 0.9% of the management fee on credit corruption, on average. Companies with the worst credit corruption levels spend 10.1% of their management fees on credit corruption. The mean of the FinTech variable is 0.002, and the standard deviation is 0.003, indicating that FinTech development in various cities in China has great differences. See Table 1 for more information on other variables. We tested the variance inflation factor (VIF) of all variables and found that the VIF test values were less than the critical value required by the rule of thumb, revealing no serious multicollinearity between variables.

We construct the mean of FinTech and credit corruption by year and city, and the scatter plot of both is shown in Fig. 3, revealing that as regional FinTech develops better, the credit corruption expenditure of companies in the jurisdiction shows a downward trend, which preliminarily illustrates the negative relationship between FinTech development and credit corruption. The identification of the causal relationship between them is verified in the following section.

Empirical results

Benchmark regression results

Table 3 presents the results of the benchmark regression on the impact of FinTech on credit corruption. The explanatory variables include a comprehensive measurement indication *Ft* based on principal component analysis and three sub-indicators: an indicator of number of FinTech companies *Ftn,* an indicator of capital of FinTech companies *Ftv*, and an indicator of financing frequency of FinTech companies *Ftf*. The estimated coefficients of all FinTech indicators are significantly negative in columns (1)–(4), when no other control variables are introduced and only year and industry effects are controlled. After the introduction of the control variables in columns (5)–(8), the sign and significance of the estimated coefficients of various FinTech indicators do not change, suggesting that FinTech can curb credit corruption and reduce companies' credit corrupt expenditures. Thus, Hypothesis 1 is supported.

Taking column (5) as an example of the economic significance of the regression coefficients, when one standard deviation increases in regional FinTech development (0.003), the companies' credit corruption expenditure in the jurisdictions decreases by an average of 6.7%[1], showing that the impact is of economic significance. As for the internal structure of FinTech, if each sub-indicator increases by one standard deviation, an increase in the number of FinTech companies (*Ftn*) contributes to a 4.4% decrease in corporate credit corruption expenditure[2]. Moreover, an increase in the capital of FinTech companies (*Ftv*) decreases corporate credit corruption expenditure by 8.8%[3]. An increase in the financing frequency of FinTech companies (*Ftf*) contributes to a 4.4% decrease[4]. Compared with the quantitative information represented by the number and financing frequency of the companies, the indicator of the capital of FinTech companies (*Ftv*) contains more information on the quality of FinTech development. Additionally, its economic effect is more than twice that of the other two indicators, showing that FinTech quality significantly contributes to its anti-corruption role.

Endogeneity issues

(i) Instrumental variable method

Regarding instrumental variables for FinTech, existing studies have developed two main ideas. The first is to directly adopt the network penetration indicator of the region as an instrumental variable (Sheng, 2021). The second is to construct an instrumental variable based on the correlation between FinTech development in the region

[1] In column (5), one standard deviation increase in *Ft* would reduce credit corruption by 0.06% (≈0.003 × 0.189), with a decrease of approximately 6.7% (= 0.06%/0.9%), for companies whose credit corruption expenditure is at the mean (0.9%).

[2] In column (6), one standard deviation increase in Ftn would reduce credit corruption by 0.04% (≈0.003 × 0.146), with a decrease of approximately 4.4% (= 0.04%/0.9%), for companies whose credit corruption expenditure is at the mean (0.9%).

[3] In column (7), one standard deviation increase in *Ftv* would reduce credit corruption by 0.08% (≈0.003 × 0.265), with a decrease of approximately 8.8% (= 0.08%/0.9%), for companies whose credit corruption expenditure is at the mean (0.9%).

[4] In column (8), one standard deviation increase in *Ftf* would reduce credit corruption by 0.04% (≈0.003 × 0.121), with a decrease of approximately 4.4% (= 0.04%/0.9%), for companies whose credit corruption expenditure is at the mean (0.9%).

Table 2
Descriptive statistics of variables.

Variables	Number of observations	Mean	Median	Standard deviation	Minimum	Maximum
Rent	10631	0.009	0.000	0.017	0.000	0.101
Ft	10631	0.002	0.001	0.003	0.000	0.010
Ftn	10631	0.003	0.002	0.003	0.000	0.010
Ftv	10631	0.001	0.000	0.003	0.000	0.010
Ftf	10631	0.002	0.000	0.003	0.000	0.010
Lev	10631	0.474	0.471	0.202	0.050	0.964
Size	10631	22.205	22.091	1.131	19.295	27.001
Growth	10631	1.210	1.109	0.563	0.380	5.124
Roa	10631	0.028	0.028	0.058	−0.277	0.197
Tang	10631	0.384	0.375	0.180	0.007	0.808
Nature	10631	0.389	0.000	0.487	0.000	1.000
Top1	10631	33.744	31.490	14.628	8.480	75.000
Director	10631	0.372	0.333	0.051	0.333	0.571
Cflow	10631	0.031	0.032	0.070	−0.212	0.240
Salary	10631	12.438	12.437	0.655	10.633	14.400

Note: This table reports the summary statistics of the key variables for the period 2011−2019. To mitigate the effect of outliers, all continuous variables are winsorised at the 1% and 99% levels.

and neighbouring cities (Li et al., 2020). Because of differences in research topics, it may be inappropriate to continue using these instrumental variables. For example, network development can directly affect the communication between local banks and companies. Thus, improving information transmission efficiency without relying on FinTech's impact generates alternative paths to credit corruption. In addition, the inherent nature of breaking spatial and temporal constraints in FinTech facilitates efficient resource flows. In this process, the cross-regional operation of FinTech businesses violates the exogeneity of the instrumental variable.

This study constructs a new instrumental variable as follows: First, we collect data on ''science and technology expenditure'' in the public finance expenditure column of all sample cities. We also use the ratio of science and technology expenditure to total fiscal expenditure as the city's fiscal science and technology expenditure intensity, *Fiscal*. Then, for any city j, we specify the other cities bordering city j in the same province. Finally, *Fiscal-iv,* the average fiscal science and technology expenditure intensity in other cities, is used as an instrumental variable for FinTech development in city j. As China accelerates as an innovative country, the original ''economic growth tournament'' is gradually transformed into a ''science and technology innovation tournament.'' Additionally, a significant strategic interaction is noted between the fiscal science and technology expenditures of each city (Zhao et al., 2021), which makes the instrumental variable *Fiscal-iv* consistent with the correlation requirement. Unlike the financial sector, which can operate across regions, a city's fiscal science and technology expenditure is used to support the development of science and technology in the local area and does not have a direct impact on other cities, thus meeting the exogeneity of the instrumental variable.

Table 4 presents the estimation results of the instrumental variable method. In the first stage of the regression in column (1), the estimated coefficient of *Fiscal-iv* is significantly positive at the 1% level, demonstrating that the instrumental variable satisfies the correlation condition. In the second stage of the regression represented in column (2), the Cragg-Donald Wald F statistic is much larger than the critical value, indicating that *Fiscal-iv* is appropriate as an instrumental variable with no weak instrumental variable problem. The coefficients of FinTech remain significantly negative after applying the instrumental variables to mitigate endogeneity bias, suggesting that FinTech can effectively curb credit corruption.

(ii) DID method.

The difference in differences method (DID) is also applied to control the endogeneity model problem with a quasi-natural experiment. On 31 December 2015, the Chinese government released the Plan for Promoting the Development of Inclusive Finance (2016−2020), which encouraged banks to provide customers with all-sided financial services that utilise emerging information technologies. Subsequently, China's financial industry began a new phase of transformation toward FinTech. As the policy was formulated by the central government, we treat it as an exogenous shock event that drives the overall development of FinTech. With differences in FinTech development in each region, the support policy may create a relatively larger shock in FinTech in less developed regions, and the marginal impact was relatively smaller in FinTech-developed regions. These differences in regional responses reflect the effects of the policy shocks. Following Cheng and Qu (2020), we used the median of the 2015-Digital Inclusive Finance Index at the city level to determine whether individuals are subject to policy shocks. The treatment group consists of cities below the median, whereas the control group consists of those above the median. The DID model is established using the following settings:

$$Rent_{i,t} = \alpha + \beta_1 Did_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_t + \gamma Controls + Year + Ind + \varepsilon_{i,t} \quad (3)$$

In Model (3), $Treat_i$ is a grouping dummy variable; $Treat_i = 1$ is for treatment group cities and $Treat_i = 0$ is for control group cities. At the

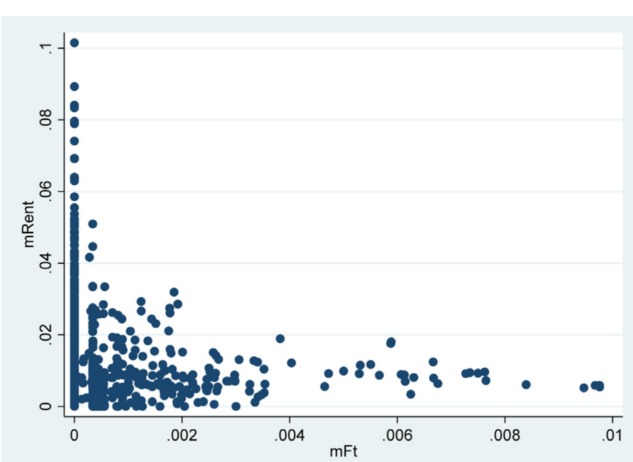

Fig. 3. The scatter plot between FinTech and credit corruption.

Table 3
Baseline regression.

	(1) *Rent*	(2) *Rent*	(3) *Rent*	(4) *Rent*	(5) *Rent*	(6) *Rent*	(7) *Rent*	(8) *Rent*
L. *Ft*	−0.194***				−0.189***			
	(−3.52)				(−3.96)			
L. *Ftn*		−0.123**				−0.146***		
		(−2.77)				(−3.56)		
L. *Ftv*			−0.323***				−0.265***	
			(−4.59)				(−4.65)	
L. *Ftf*				−0.113*				−0.121**
				(−2.22)				(−2.69)
L. *Lev*					0.006***	0.006***	0.006***	0.006***
					(6.29)	(6.30)	(6.12)	(6.33)
L. *Size*					−0.001***	−0.001***	−0.001***	−0.001***
					(−6.74)	(−6.75)	(−6.48)	(−6.87)
L. *Growth*					−0.000	−0.000	−0.000	−0.000
					(−1.52)	(−1.51)	(−1.51)	(−1.52)
L. *Roa*					0.012***	0.012***	0.012***	0.012***
					(4.43)	(4.46)	(4.43)	(4.43)
L. *Tang*					−0.002**	−0.002*	−0.002**	−0.002**
					(−2.51)	(−2.29)	(−2.56)	(−2.37)
L. *Nature*					−0.006***	−0.006***	−0.005***	−0.006***
					(−4.91)	(−4.91)	(−4.90)	(−4.93)
L. *Top1*					0.000**	0.000*	0.000*	0.000*
					(2.38)	(2.32)	(2.34)	(2.27)
L. *Director*					−0.008**	−0.008**	−0.008**	−0.008**
					(−2.94)	(−2.94)	(−2.93)	(−2.96)
L. *Cflow*					−0.009**	−0.009**	−0.009**	−0.009**
					(−3.39)	(−3.38)	(−3.37)	(−.39)
L. *Salary*					0.000	0.000	0.000	0.000
					(1.82)	(1.75)	(1.74)	(1.62)
_cons	0.009***	0.009***	0.009***	0.009***	0.033***	0.034***	0.033***	0.034***
	(7.26)	(7.27)	(7.39)	(7.00)	(9.23)	(9.68)	(9.25)	(9.12)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10631	10631	10631	10631	10631	10631	10631	10631
Adj.R^2	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5%, and 1%.

same time, $Post_t$ is a time dummy variable, with 2016 as the initial implementation point of the policy, assigned a value of 1 after 2016 and 0 before 2016. The cross term $Did_{i,t} = Treat_i \times Post_t$, with other settings, is consistent with Model (2).

In column (1) of Table 5, the estimated coefficient of $Did_{i,t}$ is significantly negative, suggesting that FinTech support policies work more significantly in less developed regions and reduce companies' expenditures on credit corruption. In column (2) of Table 5, concerning Bertrand and Mullainathan (2003), the cross terms of dummy variables for each year and grouping variable are added to the model to test the parallel trend. In column (2) of Table 5, the cross-terms before the policy (*Did2013, Did2014, Did2015*) are all insignificant. Meanwhile, the cross-terms after the policy (*Did2016, Did*2017, *Did*2018, and *Did*2019) are significant, indicating that the parallel trend hypothesis is valid. Therefore, the empirical results of the DID method are credible.

Table 4
Instrumental variable regression.

	(1)	(2)
	First stage *Ft*	Second stage *Rent*
L.*Fiscal-iv*	0.512***	
	(122.50)	
L.*Ft*		−0.209***
		(−2.61)
Year	Yes	Yes
Ind	Yes	Yes
Control variables	Yes	Yes
Cragg-Donald Wald F	15005.27	
Observations	10631	10631
Adj.R^2	0.69	0.03

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

Robustness test

(i) Controlling for the impact of anti-corruption policies and city characteristics.

Since the 18th Communist Party Congress was held in 2012, the Chinese government has developed a series of anti-corruption measures to intensify its efforts in society. Anti-corruption policies are comprehensive and focus on the financial sector to curb credit corruption. Thus, the impact of anti-corruption policies on credit corruption is similar to that of FinTech anti-corruption policies. Moreover, the negative relationship between FinTech and credit corruption may be driven by city characteristics, such as economic growth, financial development, and fiscal expenditure, in which curbing their impact is necessary. Following Li and Chan (2021), we use corruption and bribery cases filed per 10,000 public officials in each province as a proxy variable to estimate the intensity of anti-corruption policies (*Power*). We also introduce *Gdpr* (GDP growth at the city level), *Fingdp* (ratio of the loan of a financial institution to GDP at the city level), and *Expense* (ratio of local fiscal expenditure to GDP at the city level) to control for city characteristics.

In column (1) of Table 6, the estimated coefficients of *Power* are significantly negative. The results prove that anti-corruption policies effectively suppressed credit corruption. After considering the anti-corruption effect, the impact of *Ft* on *Rent* remains significantly

Table 5
Results of difference in differences estimation.

	(1) *Rent*	(2) *Rent*
Did	−0.003**	
	(−3.38)	
Treat	0.003***	0.004***
	(3.76)	(3.23)
Post	−0.002**	−0.000
	(−2.52)	(−0.09)
Did2013		0.001
		(0.60)
Did2014		−0.002
		(−1.37)
Did2015		−0.002
		(−1.25)
Did2016		−0.003*
		(−1.94)
Did2017		−0.003**
		(−2.16)
Did2018		−0.004***
		(−2.97)
Did2019		−0.006***
		(−4.02)
Year	Yes	Yes
Ind	Yes	Yes
Control variables	Yes	Yes
Observations	10631	10631
Adj.R^2	0.08	0.08

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

negative, with little change in the coefficient. In column (2), among the city variables, only the coefficient of *Fingdp* is significantly negative, indicating that traditional financial development can curb credit corruption. However, this effect does not change FinTech's significance. Finally, the impact of FinTech is still robust in column (3) when both corruption policies and city characteristics are considered.

(ii) Alternative proxies for FinTech

The Digital Inclusive Finance Index is a multidimensional digital finance evaluation index system based on massive transaction data provided by Anti Financial Services. This index covers the breadth of coverage (account coverage), the depth of use (payment, money funds, credit, insurance, investment, and credit), and the degree of

Table 6
Controlling the impact of anti-corruption policies and city characters.

	(1) *Rent*	(2) *Rent*	(3) *Rent*
L.*Ft*	−0.195***	−0.101*	−0.107**
	(−4.50)	(−2.20)	(−2.46)
Power	−0.174**		−0.179**
	(−2.60)		(−2.50)
Gdpr		0.000	0.000
		(0.50)	(0.23)
Fingdp		−0.003***	−0.003***
		(−5.97)	(−5.84)
Expense		−0.002	−0.002
		(−1.06)	(−1.13)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	10631	10631	10631
Adj.R^2	0.07	0.07	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

Table 7
Alternative proxies to FinTech.

	(1) *Rent*	(2) *Rent*	(3) *Rent*	(4) *Rent*
L.*Digindex*	−0.004***			
	(−5.10)			
L.*Coverage*		−0.004***		
		(−5.82)		
L.*Usage*			−0.002***	
			(−2.83)	
L.*Digitization*				−0.003***
				(−5.16)
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	10631	10631	10631	10631
Adj.R^2	0.07	0.07	0.07	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

digitalisation (mobile, affordable, credit, and convenience). Digital finance development is highly correlated with FinTech development. Thus, the Digital Inclusive Finance Index has been widely used as a proxy variable for FinTech in previous studies (Ye et al., 2022). Our robustness tests are conducted using the Digital Inclusive Finance Index as the explanatory variable, and the results are presented in Table 7. The estimated coefficients of the Digital Inclusive Finance Index (*Digindex*) and its sub-indices (*Coverage, Usage,* and *Digitization*) are significantly negative, indicating that the findings of the benchmark regression still hold after replacing the FinTech measurement indicator.

(iii) Alternative proxies for credit corruption.

We use the mean of *AdjFee* for companies that have not obtained loans for reasonable expenditures in the benchmark regression, in which the point estimate is identified as a company's credit corruption expenditures. Given that small deviations can be attributed to random errors, we adjust reasonable entertainment companies' expenses to an interval range and adopt the standard deviation adjustment method. We develop the variable $DFee = AdjFee - MFee$ and set *an* alternative proxy for credit corruption, $Rentd = DFee - \sigma(DFee)$ if $DFee \geq \sigma(DFee)$, and $Rentd = 0$ if $DFee < \sigma(DFee)$. Moreover, regarding Chan et al.'s (2020) model, we use operating income, instead of management expenses, to develop business entertainment expenses. We constructed an alternative proxy for credit corruption *Renti*.

Finally, in the benchmark regression, we include business entertainment expenses with credit approval in the construction of the credit corruption variable for the same year. However, with a time lag between corruption expenditure and credit approval, corruption expenditure corresponding to approved credit can originate from both the current year's expenditure and the last year's expenditure. Therefore, we construct a new credit corruption variable $Rentm_{i,t} = (Rent_{i,t} + Rent_{i,t-1})/2$, using the average of current year's expenditure and last year's expenditure to ascertain that the credit corruption variable contains information on the current and previous period. Table 8 shows the regression results for the alternative proxies of credit corruption. FinTech can also effectively curb credit corruption after replacing its construction.

(iv) Placebo test

This study assumes that expenditures on credit corruption are paid from business entertainment expenses. If this assumption holds, then other management expenses (excluding business entertainment expenses) are unrelated to credit corruption. Thus, FinTech should have no curbing effect on normal management expenses. We conduct

Table 8
Alternative proxies for credit corruption.

	(1)	(2)	(3)
	Rentd	*Renti*	*Rentm*
L.*Ft*	−0.221***	−0.017*	−0.228**
	(−5.18)	(−1.78)	(−2.26)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	10631	10631	10274
Adj.R^2	0.10	0.03	0.08

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

Table 9
Placebo test.

	(1)	(2)	(3)
	Norent	*Travel*	*Office*
L.*Ft*	0.011	0.057	−0.151
	(0.41)	(1.38)	(−1.17)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	10631	8739	8780
Adj.R^2	0.16	0.12	0.10

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

a placebo test by replacing the explained variables with the proportion of non-business entertainment expenses from total management expenses (*Norent*), the proportion of travel expenses from management expenses (*Travel*), and the proportion of office expenses from management expenses (*Office*). The estimation results in Table 9 show that FinTech has no effect on other management expenses (*Norent, Travel,* and *Office*), confirming the rationality of the credit corruption variable.

Heterogeneity analysis

Compared to traditional finance, FinTech offers greater advantages for risk identification, information mining, and inclusive development. FinTech also provides idiosyncratic effects on sample companies' credit corruption behaviour. We examine three aspects of heterogeneity: intrinsic quality, information disclosure, and regional differences.

(i) Intrinsic quality

We test the heterogeneous characteristics and intrinsic quality of companies through return on total assets (*Roa*), return on net assets (*Roe*), and rolling standard deviation of return on total assets (*Roasd*). The sample is grouped into high and low *Roa* groups[5], high and low *Roe* groups[6], and high and low *Roasd* groups[7] using the mean values of these three indicators, respectively. In Table 10, the cross terms for FinTech and each grouping variable (L.*Ft* × *Highroa*, L.*Ft* × *Highroe,* and L.*Ft* × *Lowsd*) are significantly negative, indicating that FinTech development has strengthened banks in screening companies and promoting a more efficient connection between funds and high-quality companies, thereby significantly reducing these companies to indulge in corrupt practices to obtain credit. Thus, Hypothesis 2 is supported.

(ii) Information disclosure

This study focuses on the quality of internal information disclosure, external market attention, and digital transformation in order to reflect a company's information transparency. The quality of information disclosure represents active information transparency, whereas external market attention represents passive information. Digital transformation facilitates important activities of real-time and transparent companies, such as internal management processes, R&D processes, production processes, and financial control. Inside information is required to develop the FinTech credit model.

Shanghai Stock Exchange and Shenzhen Stock Exchange in China rate the internal information disclosure of listed companies annually using grades "A, B, C, and D." The A rating of A or B is set as the high-quality information disclosure group (*Highscore* = 1), and the rest are low-quality groups (*Highscore* = 0). External market attention is measured by the research reports, which is the total number of research reports of companies analysed during the year and the samples above the mean set in the high attention group (*Attention* = 1), and otherwise set in the low attention group (*Attention* = 0). This study constructs the digital development variables of companies using text analysis by dividing the samples into a digital transformation group (the value of company digital development variables is greater than 0, *Digitisation* = 1) and a non-digital transformation group (the value of the company digital development variables is equal to 0, *Digitisation* = 0). In columns (1)–(3) of Table 11, the cross-terms (L.*Ft* × *Highscore*, L.*Ft* × *Attention,* and L.*Ft* × *Digitisation*) are all significantly negative, indicating that FinTech and the improvement of the companies' information environment have complementary effects. Moreover, an increase in company information transparency effectively enhances the curbing effect of FinTech credit corruption. Thus, Hypothesis 3 is supported. From the perspective of supporting the real economy, this result suggests that policymakers must accelerate the information improvement disclosure system and construction of the digital economy to activate the potential of FinTech.

Table 10
Heterogeneity test - intrinsic quality.

	(1)	(2)	(3)
	Rent	*Rent*	*Rent*
L.*Ft*	0.022	0.033	0.093
	(0.31)	(0.27)	(1.14)
L.*Ft* × *Highroa*	−0.391***		
	(−5.30)		
Highroa	0.001**		
	(2.89)		
L.*Ft* × *Highroe*		−0.284*	
		(−2.37)	
Highroe		0.001***	
		(6.99)	
L.*Ft* × *Lowsd*			−0.362***
			(−5.43)
Lowsd			0.001**
			(2.69)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	10631	8649	10631
Adj.R^2	0.07	0.08	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively. The grouping variable *Highroa* = 1 if the company's *Roa* is above the mean; otherwise, *Highroa* = 0. The grouping variable *Highroe* = 1 if the company's *Roe* is above the mean; otherwise, *Highroe* = 0. The grouping variable *Lowsd* = 1 if the company's *Roasd* is below the mean, and *Lowsd* = 0 otherwise.

[5] The grouping variable *Highroa* = 1 if the company's *Roa* is above the mean, otherwise *Highroa* = 0.
[6] The grouping variable *Highroe* = 1 if the company's *Roe* is above the mean, otherwise *Highroe* = 0.
[7] The grouping variable *Lowsd* = 1 if the company's *Roasd* is below the mean, otherwise *Lowsd* = 0.

Table 11
Heterogeneity test - information disclosure.

	(1) *Rent*	(2) *Rent*	(3) *Rent*
L.*Ft*	−0.021	−0.082	−0.073
	(−0.28)	(−0.95)	(−0.80)
L.*Ft* × *Highscore*	−0.203*		
	(−1.90)		
Highscore	0.000		
	(0.33)		
L.*Ft* × *Attention*		−0.203*	
		(−2.22)	
Attention		−0.001*	
		(−2.19)	
L.*Ft* × *Digitization*			−0.224**
			(−2.67)
Digitization			0.002
			(0.16)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	10631	10631	10631
Adj.R^2	0.07	0.07	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

(iii) Regional differences.

We measure regional financial development using the ratio of total deposits and bank loans to GDP. We divided the sample into a less financially developed group (*Findumy* = 1) and a financially developed group (*Findumy* = 0), based on the median indicators. Then, regional corruption is captured using the amount of corruption and bribery cases filed per 10,000 public officials. The sample is grouped into a high-corruption regional group (*Cordumy* = 1) and a low-corruption regional group (*Cordumy* = 0), based on the median. Table 12 displays the results of regional differences, where the cross term of FinTech and the two grouping variables (L.*Ft* × *Findumy* and L.*Ft* × *cordumy*) are significantly negative, demonstrating that FinTech exhibits regional 'latecomer advantage' in curbing credit corruption. Thus, Hypothesis 4 is supported.

Table 12
Heterogeneity test - regional differences.

	(1) *Rent*	(2) *Rent*
L.*Ft*	−0.082	−0.121
	(−0.56)	(−1.44)
L.*Ft* × *Findumy*	−0.282**	
	(−3.27)	
Findumy	0.001	
	(0.80)	
L.*Ft* × *Cordumy*		−0.353**
		(−3.42)
Cordumy		0.000
		(0.15)
Year	Yes	Yes
Ind	Yes	Yes
Control variables	Yes	Yes
Observations	10631	7816
Adj.R^2	0.07	0.07

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

Economic consequence analysis

(i) FinTech and credit allocation efficiency

Most scholars agree that credit corruption increases companies' financing costs and undermines the rules and order of the credit market, causing inefficient and chaotic credit allocation, which has lasting damage to the real economy (Fungáčová et al., 2015). Digital transformation by FinTech may significantly reverse the misallocation of credit resources caused by corrupt relationship chains. This section tests whether FinTech can mitigate efficiency losses caused by credit corruption.

The study argues that the sensitivity of credit to profitability reflects the efficiency of credit allocation (Covas & Den Haan, 2011). If profitable companies receive more credit funding, the allocation of credit resources will be more effective. The model used for the empirical analysis is as follows:

$$Loan_{i,t} = \alpha + \beta_1 Roa_{t-1} + \beta_2 Rent_t + \beta_3 Roa_{t-1} \times Rent_t + \gamma Controls + Year + Ind + \varepsilon_{i,t} \tag{4}$$

In Model (4), *Loan* is the bank credit scale variable, represented by the scale of corporate borrowing *Dloan*, the scale of corporate long-term borrowing *Dloanlong*, and the scale of corporate short-term borrowing *Dloanshort*. *Dloan* is defined as an increase in corporate short-term borrowing, long-term borrowing, and long-term borrowing divided by total assets; *Dloanlong* is defined as an increase in long-term borrowing divided by total assets; *Dloanshort* is defined as an increase in short-term borrowing divided by total assets; *Roa* reflects profitability; *Rent* is the credit corruption variable constructed in this study; *Controls* are the control variables, which are the same as in model (2); *Year* and *Ind* control the year effect and industry effect, respectively.

The estimated coefficient β_3 of the cross term of *Roa* and *Rent* represents the impact of corruption on credit allocation efficiency. The smaller the absolute value of β_3, the lower the efficiency losses of credit corruption. The sample is divided into a high-level FinTech group (*Ft* ≥0.002) and low-level FinTech group (*Ft* < 0.002) based on the mean of the FinTech variable. Finally, the differences in the estimated coefficient β_3 for different FinTech groups reflect the impact of FinTech on credit allocation efficiency.

As shown in Table 13, the results of the permutation test indicate that the estimated coefficients of β_3 are significantly different between the high- and low-level FinTech groups when the explained variables are total and long-term borrowing. This indicates that the moderating effect of FinTech on the "corruption - allocation efficiency" relationship improves the allocation efficiency of banks' long-term loans. However, this result is not significant for short-term loans. In columns (1)–(2), the cross term of *Roa* and *Rent* is significantly negative in both groups, and the intensity effect on the high-level FinTech group (5.185) is 48.1% smaller than that in the low-level FinTech group (9.999). The difference is statistically significant, confirming that FinTech can effectively correct the distorting effect of corruption on credit allocation. In columns (3)–(4), the intensity effect of the cross term in the high-level FinTech group is only 8% in the low-level group, and the coefficient is not significant, suggesting that FinTech has a greater moderating effect on the allocation efficiency of long-term loans. Overall, FinTech's anti-corruption effect is robust. Its development reduces credit corruption, corrects resource mismatches, and restores the dominant position of the market-oriented allocation of funds.

(ii) FinTech and corporate investment efficiency

In addition to credit allocation efficiency, credit corruption may also affect the efficiency of a company's use of funds. Theoretically, rational companies would set an optimal investment scale based on

Table 13
Economic consequence - credit allocation efficiency.

	(1) High-level FinTech group	(2) Low-level FinTech group	(3) High-level FinTech group	(4) Low-level FinTech group	(5) High-level FinTech group	(6) Low-level FinTech group
	Dloan	*Dloan*	*Dloanlong*	*Dloanlong*	*Dloanshort*	*Dloanshort*
Rent	0.611***	0.163	0.196**	0.062	0.376***	0.084
	(3.88)	(0.59)	(2.15)	(0.55)	(3.40)	(0.47)
Rent × L.*Roa*	−5.185**	−9.999**	−0.308	−3.910**	−4.155***	−4.592
	(−2.47)	(−2.18)	(−0.25)	(−2.07)	(−2.81)	(−1.57)
L.*Roa*	0.562	0.605	0.082	0.350	0.403	0.196
	(12.27)	(9.09)	(4.58)	(11.97)	(12.46)	(5.60)
Permutation test	Coefficient difference	P-Value	Coefficient difference	P-Value	Coefficient difference	P-Value
	4.814*	0.073	3.602*	0.078	0.437	0.840
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2853	5435	2853	5435	2853	5435
Adj.R^2	0.07	0.01	0.01	0.01	0.07	0.00

Note: The numbers in parentheses are T-statistics. *,**,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

the marginal return on investment equal to the marginal cost. However, aggressive companies with the intent to expand may still pay rents for corruption to obtain excess credit funds, even if they are saturated with investment, leading to over-investment inefficiency. To this end, this study tests whether FinTech can employ anti-corruption as a channel to restrain corporate over-investment.

This study uses the method proposed by Richardson (2006) to calculate corporate investment efficiency, whose basic idea is to construct a regression model to obtain a fitted value of a reasonable investment, and then use the difference between actual investment and reasonable investment to represent inefficient investment. The model fit for a reasonable investment is as follows:

$$Inv_t = \beta_0 + \beta_1 Grow_{t-1} + \beta_2 Lev_{t-1} + \beta_3 Cash_{t-1} + \beta_4 Age_{t-1} + \beta_5 Size_{t-1} + \beta_6 Rt_t + \beta_7 Inv_{t-1} + Ind + Year + \varepsilon_t \tag{5}$$

In Model (5), Inv_t is the company's investment scale, defined as Inv_t = (expenditure on the acquisition of fixed assets, intangible assets, and other long-term assets − net cash recovered from the disposal of fixed assets, intangible assets, and other long-term assets) / total assets at the beginning of the period. *Grow* is a company's growth, expressed as the operating income growth rate. *Age* is the age of the company, expressed as Ln (the year of observation period − the listing year of the company + 1). *Size* is company size equal to the natural logarithm of total assets. *Rt* is the annual return rate of corporate stock, including dividend reinvestment. *Ind* and *Year* are used to control for industry effect and year effect, respectively.

Through the regression analysis of Model (5), the sample with a residual term of more than 0 is retained, and the residual term is taken as the measurement indication of corporate over-investment. The larger the *OI*, the more severe the inefficiency caused by corporate over-investment. This study constructs the following model to analyse the impact of FinTech on the relationship between corruption and over-investment.

$$OI_{i,t} = \alpha + \beta_1 Ft_{t-1} + \beta_2 Rent_t + \beta_3 Ft_{t-1} \times Rent_t + \gamma Controls + Year + Ind + \varepsilon_{i,t} \tag{6}$$

In Model (6), *OI* is the corporate over-investment variable, and the definitions of the other variables are the same as in Model (1). The estimated results are presented in Table 14. In column (1), the credit corruption variable *Rent* is significantly positive, demonstrating that credit corruption is more likely to induce over-investment behaviour in companies. In column (2), the cross term of credit corruption and FinTech (*Rent* × L.*Ft*) is significantly negative, indicating that FinTech can restrain the interest chain of "promoting investment by corruption" and better fulfil the supervisory and disciplinary function of finance.

Conclusions and policy recommendations

FinTech is increasingly being implemented in an emerging financial innovation model, and its impact on the financial market and real economy has been widely explored by academics and practitioners. Unlike existing studies that focus on financing outcomes, this study discusses the curbing effect of FinTech on credit corruption from the perspective of digital and intelligent transformation, thereby providing new ideas and tools for anti-corruption in credit market. We use microdata of FinTech companies to construct FinTech measurement indicators at the city level in China. Moreover, we explore the impact of FinTech on credit corruption based on data from listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2019. The results show that FinTech has a significant curbing effect on credit corruption, and a one standard deviation increase in FinTech development will reduce the credit corruption expenditure of companies in jurisdictions by an average of 6.7%, which holds after accounting for endogeneity issues and conducting a series of robustness tests. Furthermore, the heterogeneity test results show that FinTech has greater advantages in risk identification, information mining, and inclusive development than traditional finance. The curbing effect on credit corruption is stronger in companies with better intrinsic quality, more transparent information disclosure, and located in less financially developed and more corrupt regions. Finally, an economic consequence analysis suggests that FinTech can correct the resource misallocation caused by credit corruption and promote corporate investment efficiency.

Considering FinTech development in China, this study has the following policy implications. First, policymakers should increase policy support for FinTech development and encourage banks to accelerate the digital and intelligent transformation of internal controls and risk management to maximise the curbing effect of FinTech on credit corruption. Financial regulators can also regularly inspect banks' credit risk control systems to strengthen technological anti-corruption. Second, this study finds that intrinsic quality and company information disclosure can significantly influence the anti-corruption effect, which fully illustrates the fundamental role of information quality in the FinTech system. Policymakers should integrate FinTech resources in various sectors, build data-sharing platforms, and provide

Table 14
Economic consequence - corporate investment efficiency.

	(1)	(2)
	OI	*OI*
Rent	0.170*	0.116
	(1.74)	(0.99)
Rent × L.*Ft*		−36.240*
		(−1.94)
L.*Ft*		−0.992**
		(−2.05)
Year	Yes	Yes
Ind	Yes	Yes
Control variables	Yes	Yes
Observations	3747	3747
Adj.R^2	0.03	0.13

Note: The numbers in parentheses are T-statistics. *, **,*** shows the significance of estimated coefficients at 10%, 5% and 1%, respectively.

multidimensional and high-quality data support for anti-corruption. Specifically, financial regulators can expand data sources to strengthen anti-corruption policies using regulatory technology. Moreover, data from multiple sectors, such as financial accounts, real estate, industry and commerce, taxation, and consumption records, can be used to conduct all-around and dead-end supervision of credit operations to form a stronger deterrent to credit corruption. Finally, FinTech has shown better application prospects in less financially developed and more corrupt regions. Therefore, policymakers should provide more targeted support. For example, it is suggested to provide more interest rate subsidies, tax incentives, and financing support to FinTech companies in these backward regions. For senior FinTech talent, housing subsidies should be offered to attract them locally. Multiple policy combinations help activate FinTech potential and accelerate the anti-corruption effects in less financially developed and more corrupt regions.

There are still some shortcomings in this study. The empirical analysis uses Chinese listed companies as a sample. However, listed companies are of relatively high quality and have fewer financing constraints, so the representation of their credit corruption behaviour is limited. We recommend taking companies in the National Equities Exchange and Quotations as a sample to reveal the impact of FinTech on the credit corruption of small- and medium-sized companies in future research. However, this study constructs indicators of credit corruption based on the assumption that only companies receiving new loans engage in credit corruption. This setting does not consider the transitional situation in which the corruption payment has been paid, and loan approval may need to wait for a long time. A questionnaire survey can directly provide information on whether companies engage in credit corruption behaviour. In future research, we will consider combining a questionnaire survey with an indicator-constructed method to improve the accuracy of credit corruption variables through the calibration of questionnaire survey information.

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