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HOW DOES THE DIGITAL ECONOMY AFFECT CORPORATE BUSINESS CREDIT SUPPLY?

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Abstract. Business credit supply entails a firm providing credit to its customers as a means to gain a competitive edge. The advent of the digital economy has brought about profound changes in business practices. In this context, it becomes crucial to examine how the digital economy impacts the business credit supply of enterprises. This study employs a theoretical framework to derive insights and carries out an empirical analysis using the City Digital Economy Development Index spanning from 2008 to 2021, along with data from A-share listed companies in Shanghai and Shenzhen. The objective is to explore the influence of the digital economy on corporate business credit supply and its underlying mechanisms. The findings reveal that the digital economy can enhance corporate business credit supply by reducing the incidence of bad debt, thus enabling companies to extend more credit to their customers. This research contributes empirical evidence for understanding the microeconomic impact of the digital economy, while also providing theoretical insights to advance the development of the digital economy and optimize the allocation of financial resources, thereby alleviating corporate financing constraints.

Keywords: digital economy, business credit, corporate business, bad debt, credit supply, digital industrialization, industry digitization.

JEL Classification: D22, G34, O16.

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1. Introduction

Commercial credit supply acts as a form of financial support for firms with ready access to financial resources, providing credit funds to those facing difficulties in obtaining such resources (Nilsen, 2002; Qu et al., 2023; Wang, 2014). It serves not only as a low-interest or interest-free loan (Qi et al., 2022) but also as a mechanism for the secondary allocation of financial resources (Qi et al., 2022; Wang, 2014). The profound integration of digital technologies, such as artificial intelligence and big data, with the economy has given rise to what is now recognized as the digital economy (Chen et al., 2022c). As the cornerstone of this digital transformation, adopting information and communication technology (ICT) intensifies competition (Stankovic et al., 2021). According to the commercial credit supply theory, enterprises are motivated to augment their commercial credit offerings, driven by objectives like boosting sales revenues (Zhou, 2022). Consequently, the digital economy is a catalyst, compelling enterprises to expand their commercial credit supply. Simultaneously, the digital economy empowers enterprises to gain a deeper understanding of every facet of the demand side of commercial credit. This enhanced comprehension enables more effective assessment, tracking, and supervision of the credit status of the demand side (Lu & Yang, 2011), ultimately reducing the incidence of bad debt in commercial credit supply. In turn, this fosters a positive cycle, encouraging enterprises to extend more commercial credit (Jory et al., 2020). Therefore, the advent of the digital economy signifies an upsurge in the supply of commercial credit to enterprises.

Over the past decade, the exploration of supply chain finance, including business credit supply, has burgeoned. However, much of this research has been rooted in a dichotomous environment, primarily focusing on the dynamics between buyers and sellers (Parviziomran & Elliot, 2023). Some literature delves into the influence of external factors, such as economic policy uncertainty, marketization degree, media reports, and analyst tracking, on the supply of business credit to enterprises (Zhou, 2022). Surprisingly, there is a noticeable dearth of discussion in the existing body of literature regarding the nexus between the digital economy and business credit supply to enterprises. Motivated by this gap, this paper positions the digital economy as a macro-environmental factor and scrutinizes its impact on corporate business credit supply. The findings contribute valuable insights and policy implications to foster the evolution of business credit supply, with the ultimate goal of mitigating corporate financing constraints.

The literature closely related to this paper encompasses research on factors influencing the supply of business credit to enterprises. Scholars have extensively studied internal factors and external environments in this regard. Regarding internal factors, studies have explored the impact of firm digital transformation (Qi et al., 2022; Zhou & Li, 2023), innovation strategies (Wu et al., 2023), promotional motives (Emery, 1984), and firm liquidity (Amberg et al., 2021; Garcia-Appendini & Montoriol-Garriga, 2013) on corporate business credit supply. For instance, firm digital transformation has been found to enhance business credit supply (Qi et al., 2022), while negative liquidity shocks can reduce it (Amberg et al., 2021). In terms of the external environment, economic policy uncertainty (Chen & Liu, 2018; Kara & Yook, 2023), monetary policy (Jiménez et al., 2012; Wan & Lee, 2023), social insurance premium payments (Chen et al., 2022a), and new technology development (Kim & Kwon, 2023; Wu et al., 2024) impact firms' commercial credit supply.

Another piece of literature related to this paper focuses on the microeconomic impact of the digital economy. Both domestic and international studies have extensively explored firm innovation, information symmetry, and firm management. The digital economy has stimulated firms' increased innovation inputs (Vatamanescu et al., 2017; Peng et al., 2023) and improved innovation output (Luo et al., 2023; Pan et al., 2022; Xia et al., 2021). Through digital technologies like cloud computing, the digital economy enhances information transparency in firms (D'Souza & Williams, 2017). Improved information transparency, in turn, can lead to enhanced corporate governance (Qi et al., 2020) and trigger internal management changes within firms (Qi & Xiao, 2020). Additionally, the digital economy can drive manufacturing development (Li, 2023).

The existing literature extensively explores the microeconomic impact of the digital economy and the factors influencing corporate business credit supply. However, there is a paucity of research specifically focused on how the digital economy affects corporate business credit supply. To address this gap, this paper incorporates the level of digital economy development into the profit function of representative enterprises. It constructs a theoretical analysis framework, proposes research hypotheses derived from theoretical analysis, and subsequently conducts an empirical investigation. The empirical test employs the city digital economy development index, measured through factor analysis spanning from 2008 to 2021, in conjunction with data from Chinese A-share listed companies from the same period. The study employs time and individual two-way fixed effects models to explore the impact of the digital economy on corporate business credit supply and its underlying mechanism. By undertaking this research, we aim to contribute to the understanding of how the digital economy influences corporate business credit supply.

The present paper makes a significant contribution in several aspects. Firstly, it expands the examination of the microeconomic impact of the digital economy by focusing on the relationship between firms and customers. While previous literature (e.g., D'Souza & Williams, 2017; Vatamanescu et al., 2017; Qi & Xiao, 2020) has primarily explored the impact of the digital economy on firm innovation, information symmetry, and firm management, this study takes a different approach. By investigating the business credit supply, the paper extends the analysis of the microeconomic impact to encompass enterprise customers. This expansion enriches the existing research on the subject. Secondly, the paper broadens the existing literature concerning business credit supply for enterprises. Prior studies have examined various factors that influence corporate credit supply, such as internal factors like digital transformation within companies (Qi et al., 2022) and external factors like the uncertainty of economic policies (Chen & Liu, 2018). In this paper, the digital economy is regarded as an external environment, and its impact on corporate business credit supply is investigated. This exploration adds to the body of knowledge surrounding the factors influencing business credit supply for enterprises. Lastly, the paper presents new evidence regarding the development of the digital economy. The findings highlight that the advancement of the digital economy can enhance the level of business credit supply for enterprises. This outcome not only benefits companies in terms of increasing sales, maintaining or expanding market share, and establishing long-term customer relationships but also facilitates the secondary allocation of financial resources and alleviates the common financing constraints faced by enterprises. Consequently, the findings contribute fresh evidence supporting the robust development of the digital economy.

The subsequent sections of this paper are organized as follows: Section 2 comprises a theoretical analysis and presents the proposed research hypotheses. Section 3 outlines the research design. Following that, Section 4 conducts empirical analysis and robustness tests. In Section 5, mechanism tests are performed to explore the topic further. Section 6 undertakes heterogeneity analysis. Finally, the paper concludes by summarizing the key findings and providing policy implications.

2. Theoretical analysis and research hypothesis

Based on the buyer's market theory, the market supply-demand relationship positions the buyer in a strong position. In this scenario, firms are inclined to provide commercial credit to their customers to facilitate the prompt sale of their products or services (Lu & Yang, 2011). In line with the theory of commercial credit supply, firms are inclined to boost their business credit offerings to augment sales revenue (Zhou, 2022). Simultaneously, the provision of commercial credit frequently encounters instances where the credit recipient faces challenges in meeting timely payments (Raj et al., 2022). While commercial credit supply has the potential to enhance sales revenue (Cao et al., 2022), it also gives rise to the conundrum of accumulating bad debts (Jory et al., 2020), thereby resulting in associated business credit costs. Consequently, the level of commercial credit supply by a firm is determined by weighing the costs and benefits associated with providing such credit (Fabbri & Klapper, 2008; Molina & Preve, 2012). Building upon this perspective, the present paper conducts a theoretical analysis of the benefits and costs of supplying commercial credit to firms.

2.1. Basic assumptions

Taking inspiration from the works of Cheng and Chen (2024) and Chen et al. (2023a), this paper establishes assumptions grounded in the context of representative firms. Subsequently, an analytical framework is constructed, and theoretical derivations are carried out.

Assumption 1: Building upon the insights of Chen et al. (2023a), this paper considers a perfectly competitive market for the product or service offered by the representative firm. In this market, the firm operates as a price taker, with the product price denoted as p. Furthermore, the unit variable cost of the product or service is represented by b, while the fixed cost is denoted as $C_0 > 0$, where $p > b$.

Assumption 2: After supplying business credit, the firm needs to manage them (Chalil & Siregar, 2021; Jin & Zhang, 2021). The level of commercial credit supply for the representative firm is denoted as L. In order to effectively manage commercial credit supply, the firm engages in daily management activities such as credit assessment and reconciliation on the demand side. Drawing upon the insights of Kopecky and Vanhoose (2004), the cost associated with managing the commercial credit supply is modeled as a quadratic cost function, specifically represented as $C(L) = lL^2/2$, where $l(>0)$ is a constant.

Assumption 3: The provision of business credit by a firm directly impacts the sales of its products or services (Lu & Yang, 2011). In accordance with the commercial credit supply theory, firms augment their business credit provision with the objective of boosting sales revenue (Zhou, 2022). This implies a direct correlation between business credit supply and heightened sales revenue, as evidenced by studies such as those conducted by Cao et al. (2022) and Lau and Schaede (2020). The sales generated by the representative firm's products or services are denoted as y. It can be expressed as $y = y_0 + dL$, where $y_0(>0)$ and $d(>0)$ are constants.

Assumption 4: A bad debt ratio is an important decision factor for firms to supply business credit to the outside world (Jory et al., 2020). The digital economy, facilitated by technologies like artificial intelligence and big data, can potentially mitigate information asymmetry (Chen et al., 2022c). In the context of the digital economy, information symmetry among enterprises is expected to improve. This enhanced information access enables enterprises to gain a better understanding of various aspects related to the demand side of commercial credit. Moreover, enterprises can effectively evaluate, track, and monitor the creditworthiness of the demand side of commercial credit (Lu & Yang, 2011). Consequently, this leads to a reduction in the incidence of bad debt associated with commercial credit supply.

The level of digital economy development is represented by D. Consequently, we can express $\mu = \mu(D)$, where μ signifies the reduction in the bad debt rate of commercial credit supply. Additionally, it is expected that $d\mu/dD < 0$, indicates a negative relationship between the development of the digital economy and the bad debt rate of commercial credit supply.

In summary, the profit of the representative firm can be expressed as $\pi = (p - b)y - K(L) - C(L) - C_0$. Hence, the objective function and constraints of the representative firm are formulated as follows:

$$\pi = (p-b)y - K(L) - C(L) - C_0; \tag{1}$$

$$s.t.\begin{cases} y = y_0 + dL, y_0 > 0, d > 0 \\ K(L) = \tau\mu L, \tau > 0 \\ C(L) = l L^2/2, l > 0 \\ \mu = \mu(D), d\mu/dD < 0 \\ C_0 > 0, p > b \end{cases}. \tag{2}$$

2.2. Model solution

The decision variable for the representative firm is the level of commercial credit supply, denoted as L. The optimal decision condition occurs when the marginal benefit derived from supplying commercial credit is equal to the marginal cost. Marginal benefits and marginal cost of commercial credit supply can be expressed by Equation (3) and Equation (4), respectively:

$$\frac{d(p-b)y}{dL} = (p-b)d; \tag{3}$$

$$\frac{d(C(L)+K(L))}{dL} = lL + \tau\mu. \tag{4}$$

By equating the right-hand sides of Equations (3) and (4), namely, ensuring that the marginal benefit of business credit supply equals the marginal cost, we arrive at the profit maximization condition for the representative firm as follows:

$$(p-b)d = lL + \tau\mu. \tag{5}$$

The optimal level of business credit supply for representative firms is obtained from Equation (5):

$$L^* = \frac{(p-b)d - \tau\mu}{l}. \tag{6}$$

In Equation (6), μ represents a function of the level of digital economic development D, while l and d are constants. Notably, p and b remain unaffected by the level of digital economic development D. To investigate the connection between the level of digital economy development D and the optimal business credit supply level L^* for enterprises, we derive the partial derivatives of both sides of Equation (4) with respect to the level of digital economy development D as follows:

$$\frac{\partial L^*}{\partial D} = -\frac{\tau}{l}\frac{d\mu}{dD}. \tag{7}$$

In Equation (7), $\tau > 0$, $l > 0$, $d\mu/dD < 0$. Therefore, it is obtained that

$$\frac{\partial L^*}{\partial D} > 0. \tag{8}$$

Equation (8) reveals that the optimal level of business credit supply, denoted as L^*, for representative enterprises, is a monotonically increasing function of the level of digital economy development *D*, acting as an external environment. With the advancement of the digital economy, the optimal level of commercial credit supply for representative enterprises has experienced a gradual rise. In light of this observation, the paper introduces the following research hypothesis.

Hypothesis 1: *The digital economy can increase the level of business credit supply of enterprises.*

3. Research design

3.1. Data sources and processing

Digitization embodies a significant historical evolutionary process (Yang et al., 2022), with the current phase initiating in 2008 (Chen et al., 2022). The empirical investigation employs a dataset from Enterprise Alert Link, encompassing city-level data up to 2021. Consequently, we focus on Chinese city data and a sample of listed companies from 2008 to 2021.

It is noteworthy that public data characterizing city digital economy development is currently unavailable. To bridge this gap, we employ factor analysis, utilizing 11 key data points sourced from Enterprise Alert Link to construct a comprehensive City Digital Economy Development Index. These data points include the Number of information and communication software and hardware enterprises, Number of Data Centers, Number of data element enterprises, Number of information and communication support enterprises, Number of colleges and universities offering emerging information and communication programs, Number of emerging information and communication programs offered by colleges and universities, Number of colleges and universities offering traditional information and communication programs, Number of traditional information and communication programs offered by colleges and universities, Number of digital primary industry enterprises, Number of digital secondary industry enterprises, and Number of digital tertiary sector enterprises.

The authoritative source of its data underpins the intentional selection of Enterprise Alert Link – China's State Administration for Market Supervision and Administration (SAMSAR). This guarantees the direct provision of accurate and reliable data. Additionally, several components of our dataset, including the Number of information and communication software and hardware enterprises, Number of Data Centers, Number of data element enterprises, Number of information and communication support enterprises, Number of digital primary industry enterprises, Number of digital secondary industry enterprises, and Number of digital tertiary sector enterprises, are sourced from Enterprise Alert Link, further reinforcing our commitment to data credibility through its affiliation with SAMSAR.

Data on the number of colleges and universities offering emerging information and communication programs, the number of emerging information and communication programs offered by colleges and universities, the number of colleges and universities offering traditional information and communication programs, and the number of traditional information and communication programs offered by colleges and universities are meticulously sourced from China's Ministry of Education. This institution, responsible for approving the establishment of colleges and universities and their programs, is considered the most authoritative source for this specific data.

The data related to listed companies are extracted from the Wind database, consolidating information from annual reports and facilitating batch downloads. Following data collection, the digital economy development index is computed for each city from 2008 to 2021. The subsequent matching of registered cities of listed companies with their respective digital economy development indices for each year involves meticulous data processing steps. These steps include eliminating samples with missing data, focusing specifically on productive enterprises (excluding financial enterprises), and filtering out samples with less than two observations. This rigorous process results in a dataset comprising 38,381 observations. A Winsorize shrinkage of 1% is applied to continuous variables to mitigate the impact of outliers.

3.2. Empirical model

To test hypothesis 1, the study employs a two-way fixed effects model that incorporates both time and individual fixed effects. This modeling approach allows for a rigorous examination of the relationship under investigation.

$$Bcrt_{it} = \alpha_0 + \beta_1 \times Deco_{it} + \eta_j \times X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}. \tag{9}$$

In the model, $Bcrt_{it}$ represents the business credit supply level of the i-th enterprise in a given year. A higher value of $Bcrt_{it}$ indicates a higher level of business credit supply. The intercept term is denoted as α_0, while α_i represents the individual fixed effect for the i-th enterprise. Furthermore, λ_t signifies the annual fixed effect for year t, and ε_{it} represents the random error term.

$Deco_{it}$ serves as the crucial explanatory variable, representing the level of digital economy development in the city where the i-th firm is located in year t. Its coefficient is denoted as β_1. If β_1 is found to be significantly positive, it suggests that the digital economy has a positive impact on the level of business credit supply for enterprises. Additionally, X_{it} represents the control variables that will be introduced later in the model.

3.3. Variable description

Drawing from existing literature (e.g., Chen et al., 2022a; Qi et al., 2022; Wu et al., 2023), the explanatory and control variables for the model were developed, following the structure presented in Table 1. These variables were carefully selected based on their relevance to the research question at hand.

Table 1. Definition of main variables

	Variable	Symbol	Definition	Reference
Dependent variables	Corporate business credit supply level	Bcrt	The ratio of sum of accounts receivable, notes receivable, prepayments and provision for bad debts to total assets	Chen et al. (2022a), Wu et al. (2023)
		rBcrt	The ratio of the sum of accounts receivable, notes receivable and prepayments to total assets	
Independent variables	Digital economy development level	Deco	The logarithm of (*Deco* + 1), where deco is the normalized value of *digidx*, the digital economy development index of the city where the enterprise is located, is measured by using factor analysis	Proposed in this study
		rDeco	Upper and lower 1% Winsorize compression values of deco	

End of Table 1

	Variable	Symbol	Definition	Reference
Control variables	Enterprise size	Size	The logarithm of total assets	Chen et al. (2022a), Wu et al. (2023)
	Profitability	Roa	Ratio of EBITDA to average total assets	Chen et al. (2022a)
	Growth	Grow	Operating income growth rate	
	Board Size	Bsize	Logarithm of the number of board members	Qi et al. (2022)
	Board Independence	Indr	Ratio of the number of independent directors to the number of board of directors	Chen and Zhang (2021)
	Two jobs in one	Dual	Chairman as well as general manager take 1, otherwise take 0	
	Institutional Investor Impact	Ist	Shareholding ratio of Institutional investors	Potter (1992)
	Shareholding Concentration	First	Percentage of shareholding of the largest shareholder	Chen and Zhang (2021)
	Duration of business existence	Age	Logarithm of (1+ Number of years of business establishment as of the year)	Chen et al. (2022a)
	Enterprise leverage	Lev	Ratio of total liabilities to total assets	Qi et al. (2022)

1. Dependent variables: The primary focus of this paper is the level of business credit supply (*Bcrt*) provided by corporates. In accounting terms, business credit represents the deferred collections resulting from the sale of goods and services to downstream customers, along with prepayments made to upstream customers (Qi et al., 2022). According to the Accounting Standards for Business Enterprises (ASBE), the asset items on a company's balance sheet are reported net of any provision for impairment, such as a provision for bad debts. Building upon the approach adopted by Chen et al. (2022a) and Wu et al. (2023), this paper employs *Bcrt* as a proxy variable for the level of business credit supply. It is calculated as the ratio of the sum of accounts receivable, notes receivable, prepayments, and provision for bad debts to total assets.

In addition, for robustness testing, *rBcrt* is derived following the methodology of Chen et al. (2022a) and Wu et al. (2023). It is defined as the ratio of the sum of accounts receivable, notes receivable, and prepayments to total assets, serving as another proxy variable for the corporate's commercial credit supply level.

2. Independent variables: The independent variable in this study is the level of digital economy development (*Deco*). Publicly available data specifically characterizing the level of digital economy development in each city is not readily accessible. The digital economy encompasses two dimensions: digital industrialization and industrial digitization (Chen et al., 2022c). To capture this multidimensional construct, the paper constructs an indicator system (outlined in Table 2) that incorporates the dimensions of digital industrialization and industrial digitization. Subsequently, factor analysis is employed to derive the digital economy

development index (*digidx*) for each city. This index serves as a comprehensive measure of the level of digital economy development in the respective cities.

Table 2. City digital economy development index

Indicators	Sub-Indicators	Data Resources	References
City Digital Economy Development Index	Digital Industrialization	Number of information and communication software and hardware enterprises	Chen et al. (2022c), Kehal and Singh (2005), Hojeghan and Esfangareh (2011)
		Number of Data Centers	
		Number of data element enterprises	
		Number of information and communication support enterprises	
		Number of colleges and universities offering emerging information and communication programs	
		Number of emerging information and communication programs offered by colleges and universities	
		Number of colleges and universities offering traditional information and communication programs	
		Number of traditional information and communication programs offered by colleges and universities	
	Industry Digitization	Number of digital primary industry enterprises	Chen et al. (2022c), D'Souza and Williams (2017), Rayna (2008)
		Number of digital secondary industry enterprises	
		Number of digital tertiary sector enterprises	

To ensure the suitability of the factor analysis method, two prerequisites, namely the Kaiser-Meyer-Olkin (KMO) test and Bartlett's spherical test, were conducted. The KMO test yielded a value of 0.788, indicating that it exceeds the recommended threshold of 0.6. Furthermore, Bartlett's test demonstrated a chi-square statistic of 61937.382 with a p-value less than 0.0001, further confirming the adequacy of the factor analysis. Among the 11 indicators examined, all met the necessary conditions for factor analysis.

Consequently, employing the factor analysis method, this paper calculated *digidx* for each city from 2008 to 2021. To ensure comparability and facilitate further analysis, *digidx* was normalized using the extreme difference standardization method. The resulting variable, *Deco*, serves as a proxy measure for the level of digital economy development. To mitigate the influence of outliers, *Deco* was further subjected to Winsorize compression, with upper and lower 1% truncation, yielding *rDeco*, which is used for robustness testing. Specifically, *rDeco* is obtained by applying the logarithm transformation to the sum of *Deco* plus 1.

Figure 1 displays the mean values of *Deco* and its growth rate from 2008 to 2021. The data illustrates a consistent improvement in the development level of the digital economy across Chinese cities during this period. In 2008, the mean value of the digital economy development level for each city stood at 0.0013, which experienced substantial growth, reaching 0.0572 in 2021. This represents a compound annual growth rate of 33.49%.

Analyzing the growth rate, it is observed that the pace of digital economy development in Chinese cities has gradually decelerated since 2009. The growth rate declined from 79.17% in 2009 to 20.84% in 2021. Despite the slowdown, the trend still signifies continuous progress in the digital economy's evolution within Chinese cities over the examined timeframe.

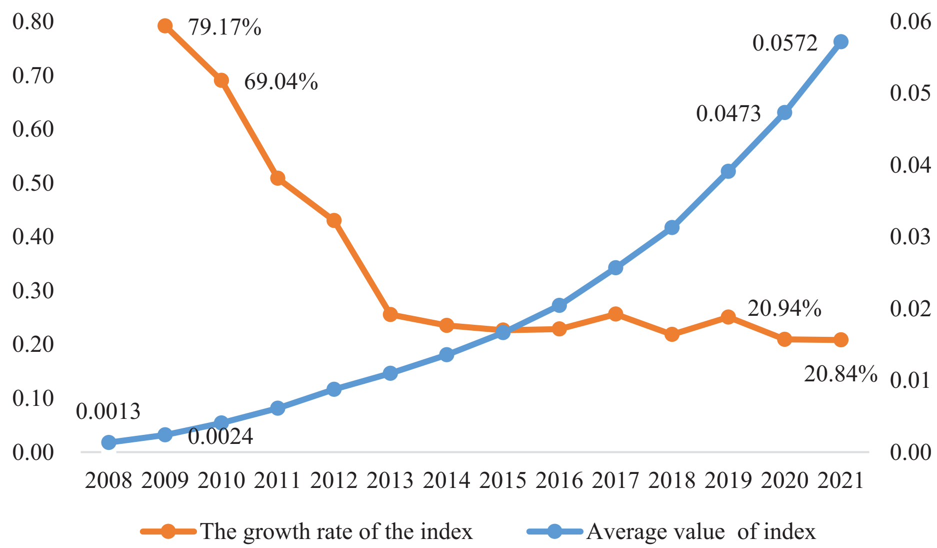

Figure 1. Average value of the normalized digital economy development index of Chinese cities and its growth rate (2008–2021)

3. Control variables. This paper incorporates various control variables based on relevant literature (e.g., Chen et al., 2022a; Qi et al., 2022; Wu et al., 2023). The selected control variables include firm size, profitability, growth, board size, firm age, and firm leverage, which have been widely recognized as influential factors. Furthermore, equity concentration, board independence, and the presence of both Chairman and General Manager are considered, as they can impact firm risk-taking (Chen & Zhang, 2021), which, in turn, may affect business credit supply. Additionally, the influence of institutional investors on firm performance (Potter, 1992) is taken into account, as it may also have an impact on business credit supply. By controlling for these variables, the analysis aims to isolate the specific relationship between the level of digital economy development and business credit supply while accounting for other relevant factors.

4. Benchmark results

4.1. Descriptive statistics

Table 3 presents the descriptive statistics of the main variables. The analysis of the descriptive statistics reveals the following key findings:

Firstly, the mean value of the business credit supply level (*Bcrt*) of enterprises, considering bad debt provision, is 0.1725. The minimum and maximum values are 0.0000 and 0.5872, respectively. These results are consistent with the characteristic of unbalanced development observed in China. Secondly, when excluding the consideration of bad debt provision, the mean value of business credit supply (*rBcrt*) of enterprises is 0.1695. The minimum and maximum values are 0.0000 and 0.5731, respectively. These findings align with the calculations reported by Chen et al. (2022a) and Wu et al. (2023). Thirdly, the mean value of firm size (*Size*) is 22.0263, measured in dollars. This result reflects the magnitude of total assets for the firms under study. Fourthly, the bad debt ratio of corporate business credit supply (*Lrat*, *rLrat*) serves as the mediating variable for the subsequent mechanism test. As outlined in ASBE, the provision for bad debts can be reversed, resulting in negative values for the bad debt ratio (*Lrat*, *rLrat*) related to corporate commercial credit supply.

These descriptive statistics provide a preliminary understanding of the distribution and characteristics of the variables in the analysis.

Table 3. Descriptive statistics of variables

Variables	Obs	Mean	Std.Dev.	Min	Max
Bcrt	38,381	0.1725	0.1251	0.0000	0.5872
rBcrt	38,381	0.1695	0.1227	0.0000	0.5731
Deco	38,381	0.1222	0.1446	0.0000	0.6931
rDeco	38,381	0.1417	0.1834	0.0001	0.8570
Lrat	38,381	0.0204	0.0834	–0.0726	1.0000
rLrat	38,381	0.0160	0.1000	–4.2266	3.1019
Size	38,381	22.0263	1.3873	14.1082	28.6365
Roa	38,381	0.0631	0.0801	–0.2331	0.4571
Grow	38,381	0.0118	0.0044	0.0039	0.0396
Bsize	38,381	2.1279	0.2164	0.0000	2.8904
Indr	38,381	0.3712	0.0601	0.0000	0.5714
Dual	38,381	0.2780	0.4480	0.0000	1.0000
Ist	38,381	0.3539	0.2446	0.0000	0.8633
First	38,381	0.3494	0.1537	0.0841	0.8000
Age	38,381	2.8798	0.3494	0.0000	4.2047
Lev	38,381	0.4322	0.2137	0.0555	0.9726

4.2. Baseline analysis

Equation (9) can be estimated using both the individual fixed effects model (FE) and the random effects model (RE). In this study, we conducted estimations using both FE and RE models and subjected the results to the Hausman test. The Hausman test yielded a chi-square statistic of 315.66 with a p-value <0.0001, indicating a significant difference between the estimates from the FE and RE models. Consequently, we employ the FE model for estimation in this paper.

Therefore, equation (9) was estimated using the FE model, incorporating a stepwise inclusion of control variables. The estimation results are presented in Table 4.

Upon analyzing columns (1)–(5) of Table 4, it is evident that the coefficients corresponding to *Deco* are all significantly positive at a 1% or 5% significance level. This indicates that the digital economy has a significant positive impact on improving the level of business credit supply for enterprises. The provision of credit to enterprises has the potential to alleviate the financing constraints faced by these businesses, thereby fostering macro-level economic growth.

This discovery holds varied implications for governments, corporate boards, and investors. Firstly, governments possess the means to alleviate corporate financing constraints by developing the digital economy. In nations like China, enterprises commonly grapple with financial limitations, impeding their growth and adversely affecting macro-level economic progress. By addressing information asymmetry and related challenges, the digital economy can streamline commercial credit provision, offering a partial remedy for financing constraints. Governments can play a pivotal role in fostering the digital economy's growth by establishing regional data centers, promoting data-sharing platforms, and actively endorsing policies such as government data openness. These measures collectively contribute to mitigating enterprise financing challenges. Secondly, corporate boards must carefully manage the scale of commercial credit supply, with the bad debt ratio assuming significance in decision-making. The digital economy, by mitigating information asymmetry and reducing information acquisition costs, encourages business managers to actively extend commercial credit externally to enhance sales revenue. However, macroeconomic fluctuations, such as economic crises, can swiftly escalate bad debt rates, offsetting the digital economy's mitigating effect. Corporate boards must, therefore, judiciously navigate the scale of commercial credit supply to prevent excessive credit provisioning from jeopardizing the business's viability. Lastly, investors must adopt a discerning approach to enterprise valuation. Financial metrics, including sales revenue, are crucial for investors assessing a business's worth. The digital economy, by facilitating increased sales revenue through expanded commercial credit supply, can enhance enterprise value. However, investors should exercise caution, recognizing that enterprise value propelled by an excessively high supply of commercial credit may lack resilience and be susceptible to rapid declines during unforeseen events. Consequently, investors should prioritize evaluating the growth rate and quality of commercial credit supply, including considerations such as bad debt provisions and their fluctuations, when gauging a company's value based on sales revenue.

Analyzing column (5) of Table 4, several noteworthy findings emerge. Firstly, the coefficient associated with firm size (*Size*) is significantly negative at a 1% significance level. This suggests that larger firms tend to have a lower level of commercial credit supply, potentially because they are less inclined to utilize commercial credit as a competitive strategy (Qi et al., 2022). Secondly, the coefficient corresponding to profitability (*Roa*) is significantly positive at a 1% significance level. This implies that higher profitability of a firm is associated with a greater level of commercial credit supply. This can be attributed to increased free cash flow resulting from enhanced profitability (Peng et al., 2021), enabling the firm to provide commercial credit to external parties more readily. Thirdly, the coefficient for growth (*Grow*) is significantly positive at a 1% significance level. This signifies that firms experiencing higher growth are more inclined to provide external commercial credit. This phenomenon can be attributed to firms utilizing the provision of commercial credit as a competitive tool to drive and sustain their growth trajectory (Wu et al., 2023). Fourthly, the coefficient related to firm leverage (*Lev*) is significantly positive at a 1% significance level. This indicates that firms with higher leverage are more likely to engage in external commercial credit activities. This may be due to the fact that elevated leverage enhances a firm's financing capability (Chen et al., 2023a), enabling it to extend commercial credit externally.

The remaining variables exhibit less significance and will not be reiterated here.

Table 4. FE estimation results for Equation (9)

Variables	(1)	(2)	(3)	(4)	(5)
	Bcrt	Bcrt	Bcrt	Bcrt	Bcrt
Deco	0.0257**	0.0336***	0.0340***	0.0344***	0.0312***
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0115)
Size		–0.0116***	–0.0115***	–0.0113***	–0.0141***
		(0.0022)	(0.0023)	(0.0023)	(0.0024)
Roa		0.0201*	0.0202*	0.0169	0.0504***
		(0.0117)	(0.0117)	(0.0118)	(0.0126)
Grow		0.8560***	0.8522***	0.8492***	0.6728***
		(0.1359)	(0.1360)	(0.1359)	(0.1361)
Bsize			–0.0028	–0.0020	0.0015
			(0.0050)	(0.0050)	(0.0050)
Indr			–0.0152	–0.0132	–0.0030
			(0.0139)	(0.0139)	(0.0139)
Dual			–0.0015	–0.0017	–0.0014
			(0.0021)	(0.0021)	(0.0021)
Ist				–0.0045	–0.0016
				(0.0034)	(0.0034)
First				0.0235*	0.0200
				(0.0122)	(0.0123)
Age					–0.0031
					(0.0099)
Lev					0.0759***
					(0.0079)
Constant	0.1770***	0.4085***	0.4186***	0.4040***	0.4274***
	(0.0024)	(0.0474)	(0.0479)	(0.0495)	(0.0531)
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	38,381	38,381	38,381	38,381	38,381
R-squared	0.0412	0.0514	0.0516	0.0522	0.0685
N	3,693	3,693	3,693	3,693	3,693

Note: * *, *, and * represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses, the same as the follows.

4.3. Robust test

The key explanatory variables presented in columns (1)–(5) of Table 4 demonstrate significant results at the 1% or 5% significance level, signifying the robustness of the findings. To further enhance the robustness of the analysis, additional tests were conducted to address endogeneity concerns, alter the measurement of explanatory variables, substitute key explanatory variables, and modify the estimation models and methods. These rigorous tests ensure the validity and reliability of the obtained results.

1. Endogeneity treatment. The theoretical analysis and empirical tests conducted in the previous section have demonstrated a significant impact of the level of digital economy development on the supply of business credit to enterprises. Conversely, as a micro-level variable, the supply of business credit by firms is unlikely to influence the macro-level variable of digital economy development. However, it is important to address potential endogeneity arising from measurement errors and other factors in the level of digital economy development. To address this concern, an instrumental variable approach is adopted, following the methodology of Chen et al. (2022b, 2022c, 2023a, 2023b), Faccio et al. (2011), Laeven and Levine (2007, 2009), and Li et al. (2020).

To construct an instrumental variable, the mean value of the level of digital economy development in other cities in the same year is calculated as *ivDeco*. Both *Deco* and *ivDeco* are susceptible to measurement errors. Therefore, *ivDeco* is correlated with *Deco*, satisfying the condition of correlation. Furthermore, the digital economy development level of other cities is unlikely to affect the business credit supply of firms in the current city, ensuring the condition of exogeneity for *ivDeco*. Utilizing *ivDeco* as the instrumental variable, Equation (9) is re-estimated using the instrumental variable method (IV). The weak instrumental variable test reveals a Cragg-Donald F-statistic of 1 500 000, surpassing the critical value of 16.38 at a 10% bias, confirming the validity of *ivDeco* as an instrumental variable.

The instrumental variable method (IV) is employed to estimate Equation (9), with *ivDeco* as the instrumental variable. The results, presented in column (1) of Table 5, reaffirm that the digital economy has a positive impact on the level of business credit supply to firms. Therefore, the robustness of the conclusion supporting hypothesis 1 is upheld when addressing endogeneity concerns.

Table 5. Robustness test of Equation (9)

Variables	(1)	(2)	(3)	(4)	(5)
	Bcrt	*rBcrt*	*Bcrt*	*Bcrt*	*Bcrt*
Deco	0.0273***	0.0335***		0.0352***	0.0379***
	(0.0062)	(0.0115)		(0.0101)	(0.0052)
rDeco			0.0212**		
			(0.0084)		
Controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	38,381	38,381	38,381	38,381	38,381
R-squared	0.0684	0.0589	0.0683	0.0472	—
N	3,693	3,693	3,693	3,693	3,693

Note: Under the maximum likelihood estimation, there is no R-squared value.

2. Change the measure of the explanatory variables. In contrast to the approach taken by Chen et al. (2022a) and Wu et al. (2023), this paper introduces a change in the measurement of the explanatory variables. Specifically, the supply of business credit to enterprises is measured without considering the bad debt provision, resulting in the variable *rBcrt*. Employing *rBcrt* as the explanatory variable, Equation (9) is re-estimated using the FE method, and the

outcomes are reported in column (2) of Table 5. Notably, the findings from column (2) corroborate the robustness of the conclusion supporting hypothesis 1.

3. Replacement of key explanatory variables. In this section, the key explanatory variable undergoes a replacement. Instead of using the normalized digital economic development index, the variable *rDeco* is derived by directly applying upper and lower 1% Winsorization. Subsequently, employing *rDeco* as the new key explanatory variable, Equation (9) is re-estimated using the fixed effects (FE) method. The results of this estimation can be found in column (3) of Table 5. Significantly, the findings from column (3) reinforce the robustness of the conclusion supporting hypothesis 1.

4. Change the estimation model. It is worth noting that certain studies (e.g., Qi et al., 2022; Wu et al., 2023) solely consider industry fixed effects and annual fixed effects when examining firms' business credit supply. In contrast, this paper re-estimates Equation (9) by additionally incorporating controls for industry fixed effects and annual fixed effects. The outcomes of this estimation can be observed in column (4) of Table 5. Notably, the results from column (4) further reinforce the robustness of the conclusion supporting research hypothesis 1.

5. Change the estimation method: In order to address potential biases associated with the estimation approach, this study employs the maximum likelihood estimation (MLE) method to re-estimate Equation (9). The outcomes of this alternative estimation procedure are displayed in column (5) of Table 5. Notably, the results from column (5) further bolster the robustness of the conclusion supporting hypothesis 1, indicating that the digital economy's positive impact on the level of business credit supply for firms holds strong under different estimation methods.

In summary, hypothesis 1 remains valid even after considering the exclusion of endogeneity, changes in the measures of the explanatory variables, replacement of key explanatory variables, and variations in the estimation model and method. These robustness tests reinforce the consistent finding that supports hypothesis 1.

5. Mechanism research

5.1. Mechanism analysis

By combining Equations (7) and (8), it becomes apparent that $\partial L^*/\partial D > 0$ owing to the fact that $d\mu/dD < 0$. The negative relationship between $d\mu/dD$ and the development level D of the digital economy indicates that the bad debt ratio μ associated with commercial credit supply for representative enterprises diminishes as the digital economy progresses. Stated differently, the enhancement of business credit supply for enterprises brought about by the digital economy is attributed to the reduction in the bad debt rate. Its mechanism for reducing the bad debt rate of business credit supply is shown in Figure 2.

The advent of the digital economy has given rise to specialized big data companies that excel in collecting multidimensional data, including information on violations and defaults across various businesses, including credit recipients. These data are then made externally available. As an illustration, FinChina (https://app.finchina.com/) located in Shanghai, China, is a prime example of such an enterprise. This company systematically gathers data from all enterprises registered in mainland China, making it accessible to the public. By simply entering the name of a specific enterprise, users can scrutinize a comprehensive set of information, including the target enterprise's tax credit rating, environmental protection credit rating, customs credit rating, as well as pertinent data on the number of judicial cases, adjudication documents, and judicial auctions associated with the specified enterprise.

In the digital economy landscape, credit scoring companies can now collect a wealth of multidimensional data on businesses, including credit recipients, for credit scoring purposes, all at a lower cost. This operational paradigm is precisely adopted by the majority of corporate credit bureaus in China. Furthermore, digital payment companies, a product of the digital economy, inherently store data related to the flow of funds from the diverse businesses they serve, including credit recipients. Take Alipay as an example; while serving as an intermediary for businesses to send and receive funds, it can systematically store transaction data from both the sender and the recipient. This stored information becomes invaluable for evaluating a business's financial capacity, forming the basis for credit assessments. Additionally, banks can capture more comprehensive data on businesses, including credit recipients, in a digital economy environment, facilitating thorough credit reviews.

In this digital economy milieu, credit providers can evaluate, track, and monitor the creditworthiness of credit recipients at a reduced cost. This is possible by using multidimensional data provided by big data companies, credit scores from credit scoring companies, data on capital flows from payment companies, and loan approvals from banks. Compared to offline operations in the non-digital economy, this comprehensive assessment allows for a more accurate selection of credit recipients with lower bad debt rates, thus reducing the bad debt rate associated with business credit supply. Following the provision of business credit, the digital environment enables more precise and frequent tracking and supervision of the creditworthiness of credit recipients at a lower cost than offline operations in the non-digital economy. This, in turn, allows for timely measures to mitigate bad debts, ultimately leading to a decrease in the bad debt rate associated with business credit supply.

The provision of commercial credit frequently encounters challenges such as credit recipients failing to meet payment deadlines (Raj et al., 2022). While an increase in commercial credit supply is associated with the potential for additional sales revenue (Cao et al., 2022), it concurrently brings about the heightened risk of accumulating bad debts (Jory et al., 2020). Consequently, the bad debt ratio is a crucial determinant for firms extending commercial credit to external entities (Jory et al., 2020). The Theory of Planned Behavior (TPB), introduced by Ajzen (1991), offers valuable insights into understanding and predicting individual behavior (Ajzen, 2020). The theory posits that attitudes toward a behavior, subjective norms, and perceived behavioral control collectively shape an individual's inclination to engage in a particular behavior (Ajzen, 1991; Hagger et al., 2022). Favorable attitudes and subjective norms, coupled with a strong perceived behavioral control, enhance an individual's willingness to execute the behavior (Ajzen, 1991; Hagger et al., 2022). In line with TPB, an individual's attitude toward a behavior reflects their positive or negative evaluation (Ajzen, 1991; Hagger et al., 2022). Consequently, reducing the bad debt rate can influence business managers to view commercial credit supply more favorably, fostering positive attitudes towards this aspect of business operations. Subjective norms, as per TPB, encompass the social pressures an individual experiences regarding the performance of a particular behavior (Ajzen, 1991; Hagger et al., 2022). Lowering the bad debt rate can result in positive perceptions of business credit provision among colleagues of business managers, thereby contributing to the formation of positive subjective norms regarding commercial credit supply. Lastly, perceived behavioral control in TPB relates to an individual's perceived ease of performing a behavior and their assessment of the feasibility of that behavior (Ajzen, 1991; Ajzen, 2020). A decline in the bad debt rate increases the likelihood of successful commercial credit recovery, reducing losses and management complexities for business managers. This improvement enhances the feasibility of expanding commercial credit supply and reinforces the perceived behavioral control of managers. In summary, by applying TPB, the digital economy plays a pivotal role in decreasing the bad debt rate associated with commercial credit supply, consequently amplifying the willingness of business managers to expand their commercial credit offerings. That is to say, as the bad debt rate diminishes, companies can extend business credit on a larger scale, fostering growth and increasing overall value. In summary, the digital economy significantly enhances the efficiency of business credit supply by mitigating the bad debt rate, a premise that forms the foundation of the paper's research hypothesis.

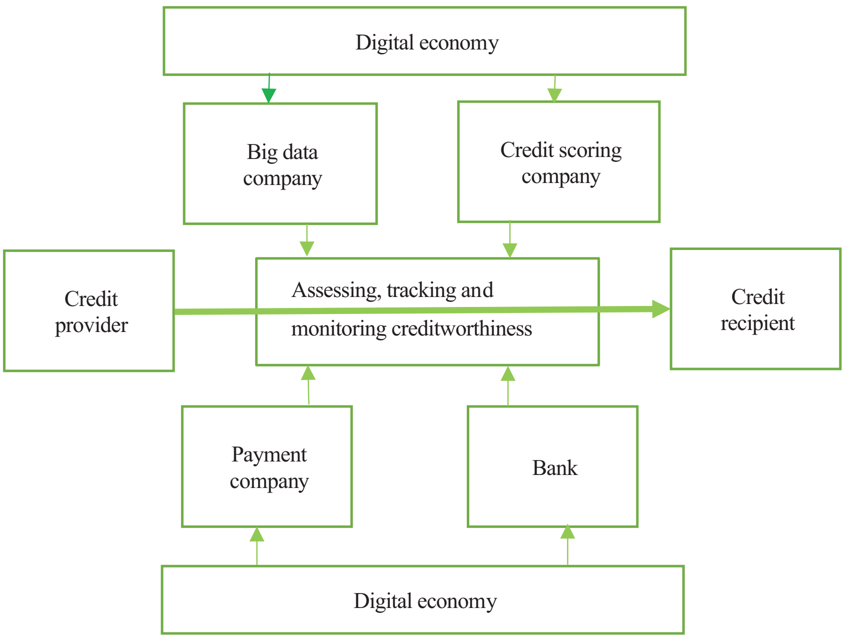

Figure 2. Mechanism of the digital economy's impact on the business credit supply for enterprises

Building upon the analyses above, this paper posits a second research hypothesis, suggesting that:

Hypothesis 2: *The digital economy improves the level of business credit supply of enterprises by reducing their bad debt rate of business credit supply.*

5.2. Mechanism Test

The preceding theoretical analysis establishes that the digital economy is crucial in augmenting corporate commercial credit supply by mitigating the bad debt ratio. To investigate and validate this influential mechanism, this paper adopts a test procedure inspired by Wen and Ye (2014) and constructs the following model, drawing upon insights from Chen et al. (2022c, 2023b).

$$Lrat_{it} = \alpha_0 + \varsigma \times Deco_{it} + \eta_j \times X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}; \quad (10)$$

$$Bcrt_{it} = \alpha_0 + \beta_1 \times Deco_{it} + \omega \times Lrat_{it} + \eta_j \times X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}. \quad (11)$$

In the proposed model, $Lrat_{it}$ represents the mediating variable, which is the bad debt rate of corporate commercial credit supply. In this study, *Lrat* is derived as a proxy variable for the bad debt rate of corporate commercial credit supply by taking the logarithm of the ratio of 1 plus provision for bad debts to the sum of provision for bad debts, accounts receivable, notes receivable, and prepayments. Additionally, for robustness testing, *rLrat* is obtained by applying upper and lower 1% Winsorize compression after calculating the ratio of provision for bad debts to the sum of provision for bad debts, accounts receivable, notes receivable, and prepayments. It is worth noting that the inclusion of the denominator is necessary since, according to the Accounting Standards for Business Enterprises, enterprises' financial statements are presented net of the provision for impairment. A higher value of *Lrat* and *rLrat* indicates a higher bad debt rate in the enterprise's commercial credit supply.

The test procedure follows these steps: Firstly, Equation (9) is estimated without incorporating any mediating variables. If the coefficient of the level of development of the digital economy is statistically significant, it indicates the presence of a total effect on corporate commercial credit supply. Conversely, if the coefficient is insignificant, it suggests a potential masking effect. Secondly, Equation (10) is estimated to examine the impact of the digital economy on the bad debt ratio of corporate business credit supply. Thirdly, Equation (11) is estimated by introducing the mediating variables. If both the coefficient ς in Equation (10) and ω in Equation (11) are statistically significant, it indicates the existence of a mediating effect. At this point, if the coefficient β_1 in Equation (11) is significant, it signifies a partial mediating effect by the mediating variable. On the other hand, if β_1 is not significant, it suggests a full mediating effect by the mediating variable. Lastly, if only one of the coefficients ς in Equation (10) and ω in Equation (11) is significant, the mediating effect can be further tested using Sobel's test.

In estimating Equation (10), the potential endogeneity of the level of digital economic development needs to be considered, similar to the previous section. Furthermore, according to theoretical analysis, the bad debt ratio of corporate commercial credit supply is believed to impact the level of corporate commercial credit supply. To measure the bad debt ratio of corporate commercial credit supply, this paper employs the bad debt provision ratio, which is often estimated by enterprises based on certain accounting assumptions while provisioning bad debts. Consequently, a degree of measurement error exists associated with the bad debt ratio of corporate commercial credit supply. Given this, the endogeneity of *Lrat* arises due to measurement error. In line with previous practices, this paper adopts the approach of calculating the mean value of the bad debt ratio of corporate commercial credit supply for other firms in the same year, resulting in *ivLrat* as an instrumental variable.

Panel A of Table 6 presents the estimation results of Equation (9) using the instrumental variable (IV) method, with *Bcrt* as the explanatory variable and *ivDeco* as the instrumental variable. In Column 1, the results for Equation (9) are displayed. Moving on to Column 2 of Table 6 Panel A, it showcases the results of estimating Equation (10) using the IV method. In this case, *Lrat* serves as the mediating variable, while *ivDeco* functions as the instrumental variable. Lastly, Column 3 in Table 6 Panel A demonstrates the results of estimating Equation (11) utilizing the IV method. In this scenario, *Bcrt* acts as the explanatory variable, while *ivDeco* and *ivLrat* are employed as instrumental variables.

The coefficient of *Deco* in column (1) of Table 6 Panel A is highly significant at a 1% level, indicating a significant aggregate effect. Similarly, in column (2), the coefficient of *Deco* is also significant at a 1% level, and in column (3), the coefficient of *Lrat* is significant at a 5% level. These findings suggest the presence of a mediating effect. By considering the sign and significance of *Deco* and *Lrat* in columns (2)–(3), we observe that the digital economy enhances corporate commercial credit supply by reducing the bad debt rate of corporate commercial credit supply. Therefore, we can conclude that the evidence supports hypothesis 2.

By substituting the mediating variable with *Lrat* and applying IV estimation to Equations (9)–(11), the corresponding outcomes are displayed in Table 6 Panel B. Likewise, by substituting the explanatory variable with *rBcrt* and employing IV estimation for Equations (9)–(11), the results are presented in Table 6 Panel C. Furthermore, by substituting the key explanatory variable with *rDeco* and employing IV estimation for Equations (9)–(11), the findings are exhibited in Table 6 Panel D. Analysis of Panels B, C, and D reveals a consistent pattern: the digital economy enhances the level of corporate business credit supply by reducing the bad debt ratio associated with corporate business credit supply. Therefore, it can be concluded that the hypothesis 2 is robust and holds under various specifications.

Table 6. Estimation results of the mechanism test

Panel A	(1)	(2)	(3)
Variables	*Bcrt*	*Lrat*	*Bcrt*
Deco	0.0273***	–0.0136***	0.0269***
	(0.0062)	(0.0052)	(0.0062)
Lrat			–0.0272**
			(0.0130)
Controls	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	38,381	38,381	38,381
R-squared	0.0684	0.0676	0.0679
N	3,693	3,693	3,693
Panel B	(1)	(2)	(3)
Variables	*Bcrt*	*rLrat*	*Bcrt*
Deco	0.0273***	–0.0128**	0.0271***
	(0.0062)	(0.0063)	(0.0062)
rLrat			–0.0164**
			(0.0070)
Controls	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	38,381	38,381	38,381
R-squared	0.0684	0.0243	0.0673
N	3,693	3,693	3,693
Panel C	(1)	(2)	(3)
Variables	*rBcrt*	*Lrat*	*rBcrt*
Deco	0.0297***	–0.0136***	0.0285***
	(0.0061)	(0.0052)	(0.0060)

End of Table 6

Panel C	(1)	(2)	(3)
Variables	*rBcrt*	*Lrat*	*rBcrt*
Lrat			–0.0842***
			(0.0079)
Controls	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	38,381	38,381	38,381
R-squared	0.0589	0.0676	0.0730
N	3,693	3,693	3,693
Panel D	(1)	(2)	(3)
Variables	*Bcrt*	*Lrat*	*Bcrt*
rDeco	0.0199***	–0.0100***	0.0197***
	(0.0045)	(0.0038)	(0.0045)
Lrat			–0.0272**
			(0.0130)
Controls	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	38,381	38,381	38,381
R-squared	0.0683	0.0676	0.0678
N	3,693	3,693	3,693

Note: All of the instrumental variables passed the validity test.

This result posits that the digital economy enhances the business credit supply of firms by reducing the bad debt rate, and hypothesis 2 is substantiated through theoretical and empirical validation. The research presented in this paper shares similarities with studies conducted by Kim and Kwon (2023) and Wu et al. (2024), which also explored the impact of emerging technologies on business credit supply to firms. Notably, Kim and Kwon's (2023) study delves into the effects of central bank digital currency on credit supply, while Wu's et al. (2024) focus on financial technology. It is worth highlighting the scarcity of research explicitly dedicated to understanding how the digital economy influences corporate business credit supply. This paper stands out as one of the few that directly investigates the impact of the digital economy on corporate business credit supply levels in the existing literature.

The proposed mechanism in this paper hinges on the assertion that the proliferation of the digital economy mitigates information asymmetry issues and enhances market efficiency (Chen & Huang, 2021; Tang, 2023). The incorporation and utilization of digital technology amplify the scope and depth of corporate information acquisition, bolstering corporations' capacity and willingness to disclose information, and concurrently diminishing information uncertainty and asymmetry (Huo & Wang, 2022). This, as depicted in Figure 2, results in a reduction in the bad debt rate associated with business credit supply. As the bad debt rate diminishes, companies can extend business credit on a broader scale, thereby fostering growth and augmenting overall value.

6. Conclusions

In this study, a theoretical analysis framework is constructed by incorporating the level of digital economy development into the profit function of representative enterprises. Based on this framework, research hypotheses are proposed, and empirical tests are conducted using the city digital economy development index and data from Chinese A-share listed companies. The analysis is performed using a time and individual two-way fixed effects model to examine the impact of the digital economy on enterprise business credit supply and its underlying mechanisms. The findings reveal that the digital economy positively influences corporate commercial credit supply by reducing the bad debt rate. This mechanism enables companies to provide more commercial credit, thereby promoting business credit supply.

Based on these research findings, several insights can be drawn. Firstly, the digital economy enhances the level of business credit supply for enterprises, benefiting the development of the demand side by alleviating financing constraints. However, caution should be exercised to avoid excessive provision of commercial credit, which may lead to cash flow crises and disruptions in the capital chain. Therefore, local financial regulators should monitor and respond to the supply of local commercial credit as regions develop the digital economy.

Secondly, the digital economy improves business credit supply by reducing the bad debt rate, which is favorable for business development. Shareholders, boards of directors, and senior managers should employ incentive mechanisms and gain a comprehensive understanding of the digital economy's mechanism to reduce information asymmetry and effectively utilize this benefit.

Thirdly, the impact of the digital economy on commercial credit supply exhibits heterogeneity, with greater significance for high-growth enterprises and financially developed regions. Consequently, shareholders and boards of directors of low-growth enterprises and those in less financially developed regions should prioritize digital transformation and seek information about upstream and downstream enterprises. By reducing the bad debt rate of commercial credit supply, these firms can improve their level of commercial credit supply.

It is worth noting that this study focuses on reducing information asymmetry and the bad debt rate of business credit supply. The potential effects of the digital economy in strengthening internal and external supervision of enterprises are not explored in this paper, representing a limitation and an avenue for future research.

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