Spatiotemporal Analysis of New Quality Productivity and Corporate Credit in China (2012-2023)

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ABSTRACT This study presents a spatiotemporal analysis of new quality productivity and corporate credit among Chinese publicly listed firms from 2012 to 2023, focusing on the high-tech sectors as representative industries. Using 25,812 firm-year observations, the study applies panel econometric models, including fixed and random effects, IV-2SLS, and System GMM, to examine how productivity improvements influence trade credit utilization and net credit positions. Results indicate that higher new quality productivity significantly reduces reliance on trade credit, while increasing the likelihood of firms acting as net creditors, reflecting improved internal financing capability and strategic credit extension to customers. Spatial analysis reveals regional clustering and spillover effects, with high-productivity provinces such as Beijing and Guangdong demonstrating stronger credit substitution patterns. Temporal trends further highlight the effects of economic cycles, policy interventions, and external shocks on the productivity-credit relationship. Framing corporate activity as a multi-node, time-resolved information system, the study offers an engineering-oriented perspective on the dynamics of resource allocation, networked interaction, and efficiency optimization in large-scale industrial systems, providing quantitative insights for strategic financial planning and policy design.

INDEX TERMS new quality productivity, corporate credit, trade credit, spatiotemporal analysis

I. INTRODUCTION

A. BACKGROUND OF THE STUDY

IN the context of rapid economic globalization and technological advancement, the competitiveness of enterprises increasingly hinges on their ability to innovate [1]. Quality productivity, which integrates aspects of innovation, efficiency, and sustainability, has become a critical factor for firms striving to succeed in the dynamic market environment [2,3]. Concurrently, access to corporate credit is vital for firms to finance operations, invest in new projects, and manage liquidity, especially in emerging economies like China [4].

China's economic landscape from 2012 to 2023 has been characterized by significant transformations, including shifts towards innovation-driven growth, implementation of supply-side structural reforms, and increased emphasis on sustainable development [5]. These changes have profound implications for both corporate productivity and financing behaviors as the industry transitions toward high-tech fiber development and automated production. However, the interplay between new quality productivity and corporate credit within China's unique economic context remains underexplored.

B. PROBLEM STATEMENT

Despite extensive research on quality productivity and corporate credit individually, there is a paucity of studies examining their interrelationship, particularly within the spatiotemporal framework of China's evolving economy [6]. Existing literature often overlooks how improvements in firms' innovation and productivity capabilities influence their reliance on trade credit and overall financial strategies. Moreover, regional disparities and temporal changes in China present additional layers of complexity that have not been thoroughly analyzed.

Understanding this relationship is crucial for policymakers aiming to foster sustainable economic growth and for businesses seeking to enhance their financial stability and competitive edge. There is a pressing need to investigate how new quality productivity affects corporate credit behaviors across different regions and over time in China.

C. RESEARCH OBJECTIVES

The primary objective of this study is to conduct a comprehensive spatiotemporal analysis of the relationship between new quality productivity and corporate credit in China from 2012 to 2023. Specific objectives include:

Examining the Impact of New Quality Productivity on Trade Credit Usage: Investigate whether improvements in new quality productivity lead to reduced reliance on trade credit among firms.

Analyzing the Effect on Net Trade Credit: Determine if higher new quality productivity influences firms to become net creditors by extending more trade credit to customers.

Exploring Regional and Industry Disparities: Assess how the relationship between new quality productivity and corporate credit varies across different regions and industries.

Understanding Temporal Trends: Analyze how this relationship evolves over time, considering economic cycles, policy interventions, and external shocks.

Providing Policy and Managerial Recommendations: Offer actionable insights for government and business leaders to promote innovation, optimize financial strategies, and achieve balanced regional development.

D. RESEARCH QUESTIONS

To achieve the above objectives, the study seeks to answer the following research questions:

What is the nature of the relationship between new quality productivity and firms' reliance on trade credit in China from 2012 to 2023?

How does new quality productivity influence firms' net trade credit positions?

What are the significant regional and industry differences in new quality productivity and trade credit usage? How have temporal changes affected the relationship between new quality productivity and corporate credit? What policy measures and business strategies can be recommended based on the findings?

II. LITERATURE REVIEW

This chapter provides a comprehensive review of the existing literature on new quality productivity and corporate credit, with a specific focus on their spatiotemporal dynamics in China from 2012 to 2023. The review critically examines prior studies, identifies gaps, and highlights how the current research addresses these gaps using novel methods and data analysis techniques. The chapter is structured to first discuss the concepts of quality productivity and corporate credit separately, followed by an exploration of their interrelationship. It then delves into the spatiotemporal aspects within the Chinese context, emphasizing the unique contributions of this study in terms of methodology, temporal scope, and geographical focus.

A. INTRODUCTION

The interconnection between quality productivity and corporate credit is a pivotal area of study in finance and operations management. Quality productivity, encompassing innovation, efficiency, and sustainability, is essential for firms aiming to enhance their competitiveness in a rapidly evolving global market. Concurrently, access to corporate credit is vital for firms to finance operations, invest in new projects, and manage liquidity [7]. Despite the significance of these two facets, existing literature has not thoroughly examined their interplay, particularly within China's unique economic landscape over the past decade. This study aims to fill this gap by providing a spatiotemporal analysis of new quality productivity and corporate credit in China from 2012 to 2023, utilizing advanced empirical methods not previously employed in this context.

B. NEW QUALITY PRODUCTIVITY

1) Definition and Theoretical Foundations

Quality productivity refers to the synergistic relationship between quality improvements and productivity gains within an organization. It posits that enhancing the quality of products or services leads to increased efficiency, cost reduction, and customer satisfaction, ultimately contributing to a firm's competitive advantage [8]. This concept is rooted in Total Quality Management (TQM) principles, which advocate for continuous improvement and customer-focused strategies [9].

Drucker introduced the "new productivity challenge," emphasizing that in the modern economy, productivity improvements must go beyond mere efficiency gains to include quality enhancements and innovation. This perspective aligns with the Resource-Based View (RBV) of the firm, which suggests that internal capabilities, such as quality and innovation, are critical resources for sustained competitive advantage.

2) Empirical Studies on Quality and Productivity

Several empirical studies have explored the relationship between quality and productivity. Bowker examined the impact of translation memory systems on productivity and quality in localization processes, finding that technology can enhance both simultaneously [10]. Gunasekaran et al. investigated how manufacturing organizations can improve productivity and quality through TQM practices, concluding that a holistic approach to quality management leads to significant gains in operational performance [11].

Desai and Shrivastava highlighted Six Sigma as a methodology that integrates quality improvement with productivity enhancement [12]. Their study demonstrated that Six Sigma initiatives result in measurable improvements in process efficiency and product quality. Similarly, Fisher found that implementing quality management practices in manufacturing settings leads to productivity gains by reducing defects and rework [13].

Vörös explored the dynamics of price, quality, and productivity improvement decisions, illustrating how firms must balance these factors to optimize performance [14]. The study emphasized that quality improvements can lead to increased productivity by enabling firms to command higher prices and capture greater market share.

While these studies provide valuable insights, they predominantly focus on Western contexts and traditional industries. There is a lack of research examining new quality productivity measures that incorporate innovation, sustainability, and technological advancements, especially within the Chinese context.

3) New Quality Productivity in the Chinese Context

China's rapid economic growth has been accompanied by a shift from labor-intensive manufacturing to innovation-driven industries. The government's policies, such as "Made in China 2025," emphasize the importance of quality and innovation in maintaining economic competitiveness. However, empirical studies examining new quality productivity in China are scarce.

Gao et al. investigated the role of institutional investor cross-ownership in promoting corporate innovation in China. Their findings suggest that shared ownership structures can facilitate knowledge transfer and collaborative innovation efforts, enhancing quality productivity. However, their study does not directly link these improvements to corporate credit access or consider spatiotemporal variations.

Li et al. analyzed digital finance and enterprise financing constraints in China, highlighting how technological advancements can alleviate financing difficulties for firms. While the study touches on productivity improvements through digitalization, it does not specifically address new quality productivity or its impact on corporate credit.

The current study addresses these gaps by focusing on new quality productivity measures that encompass innovation, sustainability, and governance, and by examining their relationship with corporate credit in China over a significant temporal span.

III. METHODOLOGY

This chapter outlines the research methodology employed to investigate the relationship between corporate trade credit and new quality productivity. It details the data sources, variable definitions, model specifications, and the rationale for choosing the specific econometric models. The methodologies align with established practices in financial and productivity research, ensuring the reliability and validity of the findings.

A. DATA SOURCES

The study utilizes a comprehensive dataset extracted from publicly listed companies' financial statements and reports from 2012 to 2023. The primary data sources include:

- Corporate Financial Reports: Annual financial statements provide detailed information on assets, liabilities, equity, revenues, expenses, and cash flows. Key items such as accounts receivable, accounts payable, notes receivable, notes payable, prepaid accounts, and advance receipts are obtained from these reports.
- Corporate Social Responsibility (CSR) Reports: These reports offer insights into companies' sustainable practices, environmental initiatives, and social contributions, which are crucial for assessing new quality productivity.
- Patent Databases: Information on corporate patents, including the number of patents, types, and areas of innovation, is gathered from national patent offices and specialized databases.
- Human Resources Disclosures: Data on the proportion of research and development (R&D) personnel and employees with advanced degrees are collected from company disclosures and social responsibility reports.
- Environmental, Social, and Governance (ESG) Ratings: ESG scores and related environmental governance metrics are sourced from reputable rating agencies.

These diverse data sources ensure a multidimensional assessment of corporate performance, aligning with the methodologies used in previous studies Jaffe1995, WangWang2021.

B. VARIABLE DEFINITIONS

1) Trade Credit Variables

2) Commercial Credit

Commercial credit reflects a company's ability to utilize interest-free liabilities and is calculated as the ratio of certain current liabilities to total assets. The formula is as follows:

$$\begin{aligned}\text{Commercial Credit}_{it} &= \text{Accounts Payable}_{it}\\ &\quad + \text{Notes Payable}_{it}\\ &\quad + \text{Advance Receipts}_{it}.\end{aligned}$$

- Accounts Payable: Obligations to pay for goods or services acquired.
- Notes Payable: Written promises to pay a specific sum.
- Advance Receipts: Payments received before the delivery of goods or services.
- Total Assets: The sum of current and non-current assets on the balance sheet.

3) Net Commercial Credit

Net commercial credit accounts for both the credit a company receives and extends, providing a net financing position:

$$\begin{aligned}\text{Net Commercial Credit}_{it} &= \text{Commercial Credit}_{it}\\ &\quad - \text{Accounts Receivable}_{it}\\ &\quad + \text{Notes Receivable}_{it}\\ &\quad + \text{Prepaid Accounts}_{it}.\end{aligned}$$

- Accounts Receivable: Money owed by customers.
- Notes Receivable: Written promises to receive a specific sum.
- Prepaid Accounts: Payments made in advance for future expenses.

4) New Quality Productivity Variables

New quality productivity is a composite measure of a company's innovation efficiency and technological output. To ensure a rigorous measurement framework, we distinguish between productivity (output/efficiency indicators) and governance/inputs. While previous studies sometimes conflated these, we now define new quality productivity primarily through efficiency-oriented metrics.

Refined Indicators Used for Productivity (Output/Efficiency):

Innovation Efficiency: Measured by the ratio of patent outputs to R&D investment (Total Factor Productivity – TFP approach).

Proportion of Highly Educated Employees: Reflects the quality of human capital applied to production.

Environmental Governance Outcomes: Derived from actual carbon reduction and resource recycling efficiency (sourced from ESG ratings).

Green Technology Conversion: The ratio of green patents applied in actual production.

Governance and Input Factors (Reclassified as Control or Antecedent Variables):

Management's Environmental Awareness and Executives with Overseas Background are now treated as corporate governance drivers that facilitate the adoption of new quality productivity, rather than components of the productivity score itself.

5) New Quality Productivity (Entropy Method)

This measure uses the entropy weighting method to assign weights to various indicators, ensuring objectivity in the composite score Shahin2008, Gunasekaran1998:

$$\text{New Quality Productivity}_{it}^{\text{entropy}} = \sum_{j=1}^{n} w_j x_{jit}.$$

- w_j: Weight of the jth indicator derived from entropy calculations.
- x_{jit}: Actual value of the jth indicator for firm i at time t.

6) New Quality Productivity (Reference Weight Method)

This approach applies weights from established literature to the indicators Bowker2005, Drucker2018:

$$\text{New Quality Productivity}_{\text{Reference},it} = \sum_{j=1}^{n} w_j^{\text{ref}} x_{jit}.$$

- w_j^{ref}: Weight of the jth indicator as per existing studies.

7) Indicators Used

1. Proportion of R&D Personnel: Indicates innovation capacity.

2. Proportion of Highly Educated Employees: Reflects human capital quality.

3. Management's Environmental Awareness: Assessed through disclosures.

4. Executives with Overseas Background: Denotes diverse expertise.

5. Environmental Governance Score: Derived from ESG ratings.

6. Fixed Asset Ratio: Represents investment in long-term assets.

7. Capital Accumulation Rate: Growth rate of capital investments.

8. Innovation Level: Measured by patent counts and innovation outputs Gao2019.

9. Digitalization Degree: Investment in IT and digital infrastructure.

10. Intangible Asset Ratio: Proportion of intangible assets like patents and trademarks.

11. Green Technology Level: Investments and outputs in eco-friendly technologies WangWang 2021.

12. Proportion of Green Patents: Ratio of green patents to total patents.

C. MODEL SPECIFICATION

1) Econometric Model

To examine the impact of new quality productivity on corporate trade credit, we employ panel data regression models. The general form is:

$$\text{Trade Credit}_{it} = \alpha + \beta_1 \text{New Quality Productivity}_{it} + \beta_2 \text{Controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it}.$$

Where:

- Trade Credit_{it}: Commercial credit or net commercial credit of firm i at time t.
- $\text{New Quality Productivity}_{it}$: New quality productivity score.
- Controls_{it}: Vector of control variables such as firm size, leverage, and profitability.
- α: Intercept term.
- β_1, β_2: Coefficients to be estimated.
- μ_i: Unobserved firm-specific effect.
- λ_t: Time-specific effect.
- ε_{it}: Error term.

2) Fixed Effects and Random Effects Models

3) Fixed Effects Model

The fixed effects model accounts for unobserved heterogeneity by allowing the intercept to vary across firms but remain constant over time for each firm Greene2012:

$$\text{Trade Credit}_{it} = \alpha_i + \beta_1 \text{New Quality Productivity}_{it} + \beta_2 \text{Controls}_{it} + \lambda_t + \varepsilon_{it}.$$

- α_i: Firm-specific intercept capturing time-invariant characteristics.

This model is appropriate when the unobserved individual effects μ_i are correlated with the independent variables.

4) Random Effects Model

The random effects model assumes that the individual-specific effects are random and uncorrelated with the independent variables:

$$\begin{aligned}\text{Trade Credit}_{it} = \alpha + \beta_1 \text{ New Quality Productivity}_{it} \\ + \beta_2 \text{ Controls}_{it} + \mu_i + \lambda_t + \boldsymbol{\varepsilon}_{it}.\end{aligned}$$

- μ_i: Random error component specific to firm i.

The choice between fixed and random effects models is determined using the Hausman test Hausman1978, which tests whether the unique errors are correlated with the regressors. Notably, this study applies the Random Effects (RE) model to the Trade Credit (TC) analysis and the Fixed Effects (FE) model to the Net Trade Credit (NTC) analysis. This logical distinction stems from the fundamental difference in the nature of the dependent variables.

The underlying theoretical explanation for this discrepancy lies in the "firm-specific heterogeneity" captured by the error terms. In the Trade Credit model, which measures a firm's total utilization of external short-term liabilities, the factors influencing these decisions (such as industry norms or long-term supplier trust) are often relatively stable and may not be strongly correlated with time-varying productivity indicators. Thus, the individual effects can be treated as random draws from a population, satisfying the RE assumption. In contrast, Net Trade Credit (NTC) reflects a firm's strategic "net position" in the supply chain (credit extended minus credit received). This positioning is deeply intertwined with idiosyncratic, unobserved firm characteristics—such as management's specific risk appetite, bargaining power, and internal financial constraints—which are highly likely to be correlated with the firm's innovative capabilities and New Quality Productivity. Consequently, the Hausman test tends to reject the null hypothesis for the NTC model, necessitating the use of FE to control for these endogenous, time-invariant firm-specific factors to ensure unbiased estimates.

D. MODEL SELECTION AND STATISTICAL TESTS

1) Hausman Test

The Hausman test assesses whether the random effects estimator is consistent:

- Null Hypothesis (H_0): Random effects model is appropriate (no correlation between μ_i and regressors).
- Alternative Hypothesis (H_1): Fixed effects model is appropriate (correlation exists).

The test statistic is:

$$H = (\text{RE} - \text{FE})'[\text{Var}(\text{FE}) - \text{Var}(\text{RE})]^{-1}(\text{RE} - \text{FE}).$$

Where:

- RE : Coefficient estimates from the random effects model.
- FE : Coefficient estimates from the fixed effects model.

A significant H statistic leads to rejection of H_0, favoring the fixed effects model. To detect multicollinearity among independent variables, we calculate the Variance Inflation Factor (VIF):

$$\text{VIF}_j = \frac{1}{1 - R_j^2}.$$

Where R_j^2 is the coefficient of determination from regressing the jth independent variable on all other independent variables. A VIF value exceeding 10 indicates significant multicollinearity Greene2012.

E. MODEL ESTIMATION PROCEDURES

1) Ordinary Least Squares (OLS) Regression

For initial analysis, we use OLS regression to estimate the relationship:

$$\begin{aligned}\text{Trade Credit}_{it} = \alpha + \beta_1 \text{ New Quality Productivity}_{it} \\ + \beta_2 \text{ Controls}_{it} + \boldsymbol{\varepsilon}_{it}.\end{aligned}$$

OLS regression provides a baseline understanding of the relationship between variables. However, it may yield biased estimates if unobserved heterogeneity exists or if the error terms are correlated with the independent variables.

2) Panel Data Estimation

Given the panel nature of the data, we employ:

- Fixed Effects Estimation: Controls for time-invariant unobserved heterogeneity by demeaning the data. This method is appropriate when individual effects are correlated with the regressors PetersenRajan1994.
- Random Effects Estimation: Uses generalized least squares (GLS) to account for both within and between variations. This method is efficient if individual effects are uncorrelated with the regressors Greene2012.

The estimation procedure involves:

1. Estimation of OLS Model: To get initial parameter estimates and identify potential issues.

2. Conducting Hausman Test: To decide between fixed and random effects models based on the correlation of individual effects and regressors.

3. Estimating Fixed or Random Effects Model: Based on the Hausman test results, we estimate the appropriate model to obtain consistent and efficient estimates.

F. ROBUSTNESS CHECKS

We conduct several robustness checks to validate the results:

- Heteroskedasticity-Consistent Standard Errors: We adjust standard er- rors using White's correction White1980 to account for heteroskedasticity, en- suring the validity of inference.
- Serial Correlation Tests: We perform Wooldridge's test Wooldridge2010 for autocorrelation in panel data to detect any serial correlation in the error terms. If present, we adjust the standard errors accordingly.

- Alternative Model Specifications: We test the models by including lagged dependent variables or using alternative measures of productivity to check the robustness of the results.

G. ECONOMETRIC ISSUES AND SOLUTIONS

1) Endogeneity and Dynamic Panel Analysis

Endogeneity is a primary concern in this study, potentially arising from reverse causality (e.g., whether higher productivity reduces trade credit reliance or whether credit constraints force firms to innovate), omitted variable bias, or measurement errors. To rigorously address these issues beyond standard fixed effects, we implement the following:

- Instrumental Variable (IV) approach with 2SLS: We utilize the industry-province-year average of new quality productivity as an instrument for firm-level productivity. This external measure is correlated with firm-level innovation due to regional-industry clusters but remains exogenous to individual firm credit decisions.
- System GMM (Generalized Method of Moments): To account for the dynamic nature of corporate financial decisions, where past trade credit levels may influence current ones, we employ a System GMM model. This model addresses the endogeneity of the productivity variable by using its lagged levels and differences as internal instruments, while also controlling for firm-level fixed effects and time-invariant unobservables.
- Lagged Independent Variables: Incorporating lagged values of independent variables can help address potential reverse causality.

2) Non-Stationarity

Given the time series component, variables may be non-stationary, leading to spurious regression results. We ensure stationarity by:

- Differencing: If unit root tests indicate non-stationarity, we difference the variables to achieve stationarity.
- Panel Unit Root Tests: We use panel-specific tests like Levin-Lin-Chu (LLC) test to confirm stationarity across panels.

3) Sample Selection Bias

To address potential sample selection bias:

- Heckman Two-Step Procedure: We first estimate a selection equation using a probit model to model the probability of a firm's inclusion in the sample. In the second step, we include the inverse Mills ratio in the main regression to correct for selection bias Heckman1979.

4) Multicollinearity

High multicollinearity among independent variables can inflate standard errors and make coefficient estimates unreliable. We address this by:

- Checking VIF Values: Variables with high VIF values are examined, and if necessary, variables are transformed or dropped.
- Principal Component Analysis (PCA): We use PCA to reduce dimensionality and construct uncorrelated factors from correlated variables.

IV. EMPIRICAL ANALYSIS

This chapter conducts an in-depth empirical analysis of the relationship between corporate trade credit and new quality productivity. Using descriptive statistics, correlation analysis, and regression models, we explore the characteristics and interaction mechanisms of key variables in detail. To ensure comprehensiveness and rigor, we provide detailed interpretations of important results in each table and figure.

A. DESCRIPTIVE STATISTICAL ANALYSIS

1) Basic Characteristics of Key Variables

First, we perform descriptive statistics on the core variables: New Quality Productivity (Entropy Method), New Quality Productivity (Reference Weight), Trade Credit, and Net Trade Credit. The results are shown in Table 1.

TABLE 1. Descriptive Statistics of Key Variables

Norm	New quality productivity (entropy method)	New quality productivity (reference weights)	Business credit	Net business credit
Count	25,812	25,812	25,812	25,812
Mean	8.3789	5.7174	0.1504	-0.0246
Std	9.3832	2.9719	0.1078	0.1215
Min	1.0709	1.5041	0	-0.6736
25% quartile	3.4564	3.6629	0.0689	-0.0928
50% quartile	5.4601	4.9479	0.1242	-0.0218
75% quartile	9.1447	6.9803	0.2078	0.0421
Max	63.0449	16.3546	0.7671	0.6228

From Table 1, we observe that the New Quality Productivity (Entropy Method) has a mean of 8.3789 and a standard deviation of 9.3832, with a minimum of 1.0709 and a maximum of 63.0449. This indicates significant differences in productivity levels among sample firms, with some firms having outstanding advantages in new quality productivity. The New Quality Productivity (Reference Weight) has a mean of 5.7174, a standard deviation of 2.9719, a minimum of 1.5041, and a maximum of 16.3546, showing a more concentrated distribution compared to the entropy method.

The Trade Credit has a mean of 0.1504, implying that, on average, trade credit accounts for 15.04% of firms' transactions. The standard deviation is 0.1078, with values ranging from 0 to 0.7671, indicating variability in the extent of trade credit usage among firms. Some firms do not use trade credit at all, while others rely heavily on it. The Net Trade Credit has a mean close to zero (-0.0246), with a standard deviation of 0.1215, suggesting that most firms have a balance between accounts payable and accounts receivable, though some are net creditors or net debtors.

2) Distribution Characteristics of Variables

To visually understand the distribution of each variable, we plotted the corresponding histograms. From Figure 1, the

New Quality Productivity (Reference Weight) data mainly concentrates between 4 and 6, showing a right-skewed distribution. Most firms have medium levels of new quality productivity, while a few have higher productivity levels exceeding 10, and very few reach above 16, indicating significant advantages in new quality productivity.

Figure 2 shows that the New Quality Productivity (Entropy Method) data is concentrated between 0 and 10, also presenting a right-skewed distribution. While most firms have lower productivity levels, a few exceed 20, and some even reach above 60, further confirming the uneven distribution of productivity levels among firms.

From Figure 3, the Trade Credit data is mostly concentrated between 0.1 and 0.2, showing a typical right-skewed distribution. Most firms use trade credit moderately, while a few have trade credit ratios exceeding 0.3, even up to 0.7. Some firms have a trade credit ratio of zero, possibly adopting cash transactions or prepayment models.

Figure 4 shows that the Net Trade Credit data presents a normal distribution with a peak around zero, indicating that most firms have a balance between accounts receivable and accounts payable. The distribution is symmetrical, suggesting firms can be net creditors or net debtors. Extreme values are rare, with very few firms having net trade credit exceeding ± 0.6.

B. SPATIOTEMPORAL INTEGRATION AND REGIONAL DIFFERENCES ANALYSIS

1) Spatial Clustering and Regional Disparities

To understand the usage of trade credit across industries, we ranked the industries based on their average trade credit, as shown in Figure 5.

From Figure 5, the Construction Industry ranks first with the highest average trade credit, reflecting the widespread use of deferred payments and installment settlements in this sector. Following closely are the Construction Installation Industry and Building Decoration Industry, both closely related to construction and similarly dependent on trade credit. The Civil Engineering Construction ranks fourth, closely associated with large infrastructure projects requiring significant capital, leading to high trade credit usage. The Ferrous Metal Smelting and Rolling Industry ranks fifth, due to extensive use of trade credit in raw material procurement and product sales.

Additionally, the Automobile Manufacturing and Electrical Machinery and Equipment Manufacturing industries rank sixth and seventh, indicating frequent trade credit transactions among upstream and downstream firms in complex manufacturing supply chains. The Other Manufacturing, Wholesale Trade, and Metal Products Industry also make the top ten, suggesting that firms in these sectors commonly use trade credit to facilitate transactions and fund circulation.

While the Top 10 rankings (Figures 5-8) illustrate geographical variations, the data further reveals a clear spatial correlation. High-productivity clusters in the Yangtze River Delta and the Pearl River Delta demonstrate that new quality productivity does not exist in isolation; rather, it exhibits a 'neighboring effect' where firms in technologically advanced hubs benefit from regional knowledge spillovers. This spatial concentration suggests that the observed inverse relationship between productivity and trade credit reliance is more pronounced in regional clusters with mature financial infrastructures and high innovation density.

2) Top 10 Industries by Average New Quality Productivity

To explore the performance of new quality productivity across industries, we ranked industries based on their average new quality productivity, as shown in Figure 6.

Figure 6 shows that the Ecological Protection and Environmental Management Industry ranks first with the highest average new quality productivity. This is due to the country's emphasis on ecological environment and strong policy support, promoting technological innovation and productivity improvements in this sector. The Agriculture, Forestry, Animal Husbandry, Fishery Services rank second, reflecting the widespread application of modern agricultural technologies and the development of agricultural industrialization. The Science and Technology Promotion and Application Services rank third, directly related to technological innovation and high levels of new quality productivity.

Other industries in the top ten include Culture and Arts, Electricity and Heat Production and Supply, Education, Water Production and Supply, Postal Industry, Health and Social Work, and Scientific Research and Technical Services. These industries mostly belong to high-tech and public service sectors, demonstrating the country's significant investment and attention in technological innovation and livelihood sectors.

3) Top 10 Provinces by Average Trade Credit

To understand the usage of trade credit across regions, we ranked provinces based on their average trade credit, as shown in Figure 7.

From Figure 7, Anhui Province ranks first with the highest average trade credit, likely due to its industry structure dominated by manufacturing and construction, which heavily rely on trade credit. Shaanxi Province and Xinjiang Uygur Autonomous Region rank second and third, benefiting from national support under the Western Development policy, with numerous infrastructure and resource development projects leading to frequent trade credit usage.

Hubei Province, Heilongjiang Province, and Jiangsu Province also make the top ten, with active credit transactions among firms due to their developed economies. The Hong Kong Special Administrative Region ranks ninth, reflecting its mature trade credit system and sound legal environment, conducive to credit transactions. Inner Mongolia Autonomous Region ranks tenth, closely related to its abundant natural resource development and related industry growth.

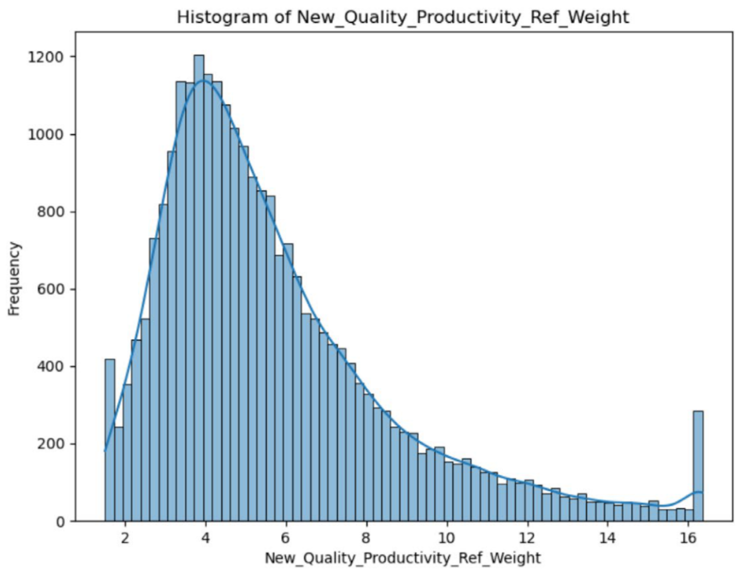

FIGURE 1. Histogram of New Quality Productivity (Reference Weight)

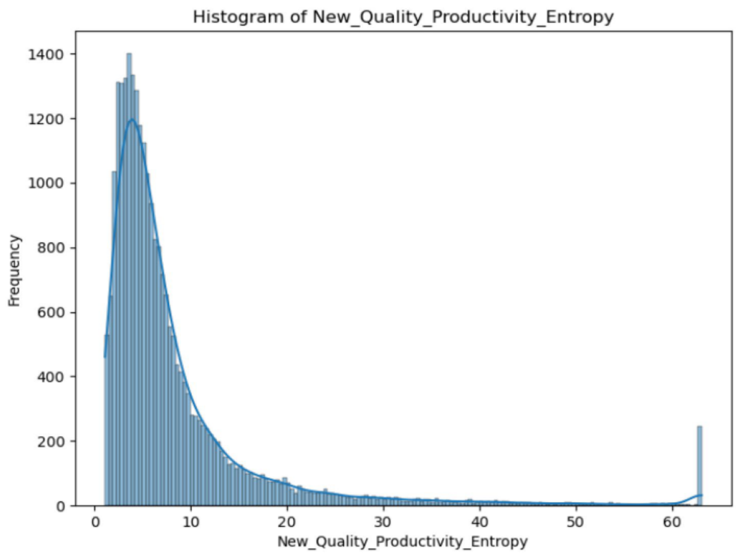

FIGURE 2. Histogram of New Quality Productivity (Entropy Method)

4) Top 10 Provinces by Average New Quality Productivity

To analyze the distribution of new quality productivity across regions, we ranked provinces based on their average new quality productivity, as shown in Figure 8.

Figure 8 shows that Beijing ranks first with the highest average new quality productivity. As the national center for technological innovation and education, Beijing has abundant higher education institutions and research organizations, with rich technological innovation resources and significant RD investment. The Inner Mongolia Autonomous Region ranks second, benefiting from the combination of resource development and high-tech applications, promoting the improvement of new quality productivity. Hunan Province and Hubei Province rank third and fourth, respectively. These regions have numerous universities and research institutions, such as Central South University, Hunan University, Wuhan University, and Huazhong University of Science and Technology, providing strong talent and technical support for regional innovation. Guangdong Province ranks fifth, actively promoting industrial upgrading and technological innovation as an economic powerhouse and manufacturing center, with substantial increases in

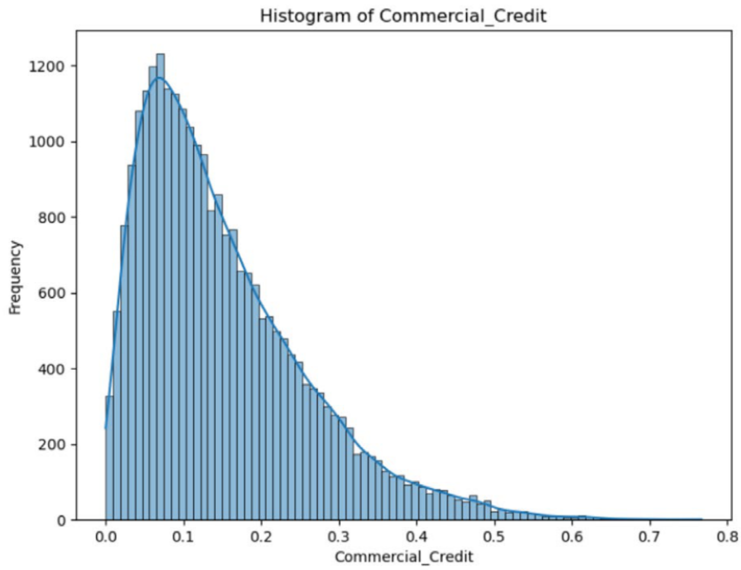

FIGURE 3. Histogram of Trade Credit

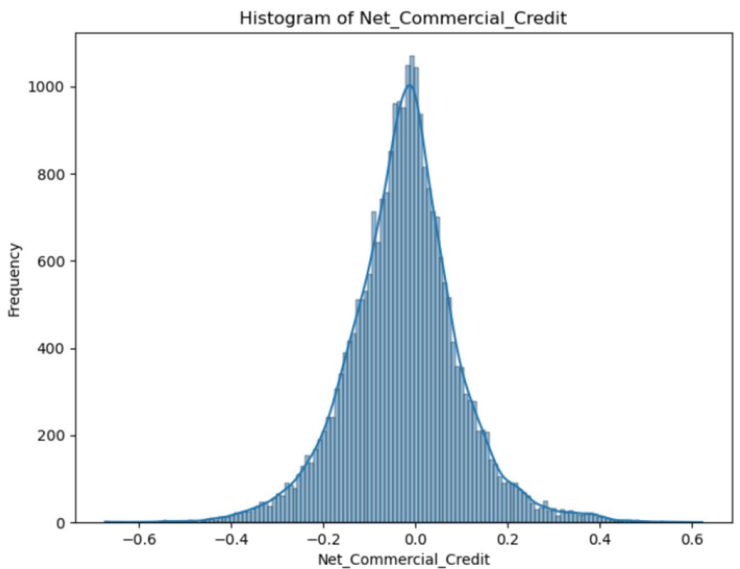

FIGURE 4. Histogram of Net Trade Credit

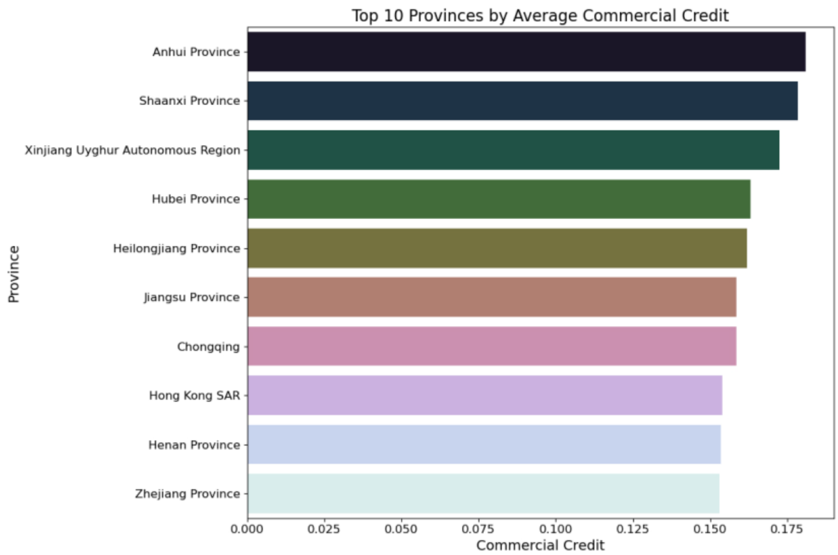

FIGURE 5. Top 10 Industries by Average Trade Credit

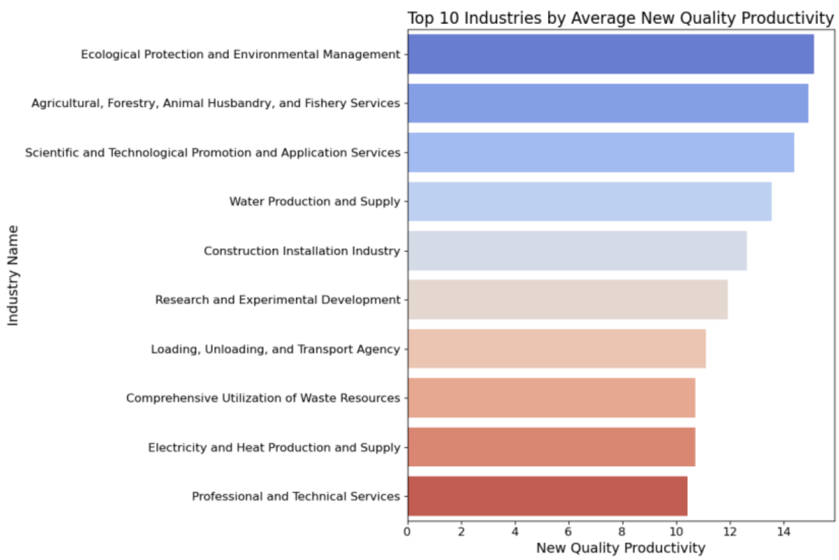

FIGURE 6. Top 10 Industries by Average New Quality Productivity

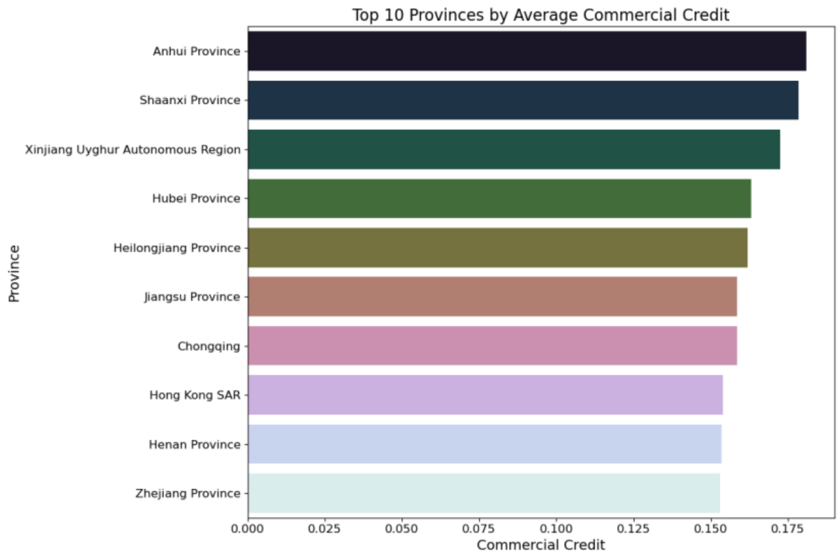

FIGURE 7. Top 10 Provinces by Average Trade Credit

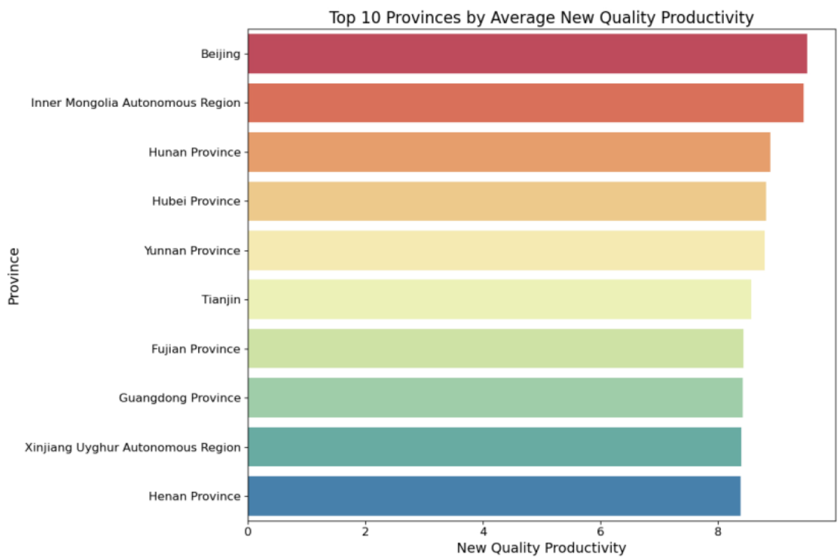

FIGURE 8. Top 10 Provinces by Average New Quality Productivity

technological investment.

Other provinces in the top ten include Xinjiang Uygur Autonomous Region, Zhejiang Province, Shaanxi Province, Henan Province, and Guangxi Zhuang Autonomous Region. These regions show outstanding performance in new quality productivity, reflecting the effectiveness of the national re gional coordinated development strategy and the high imp ortance attached to technological innovation across the count ry.

C. TIME TREND ANALYSIS

1) Average Trade Credit Over Different Periods

To understand the trend of trade credit over time, we plotted the average trade credit from 2012 to 2023, as shown in Figure 9.

From Figure 9, the average trade credit in 2012 was relatively low, about 0.12, related to the fact that China's market credit system was still in the improvement stage at that time. From 2012 to 2016, trade credit gradually increased, reaching a peak of about 0.16 in 2016. During this period, the country actively promoted supply-side structural reforms and improved the financial environment, increasing credit transactions among firms.

After 2016, trade credit fluctuated, decreasing to about 0.14 in 2018. This was influenced by deleveraging policies and stricter financial regulations, tightening corporate financing channels and somewhat limiting credit transactions. After 2020, trade credit remained relatively stable and slightly rebounded between 2021 and 2023. This was due to the country's implementation of proactive fiscal policies and prudent monetary policies to support the real economy, promoting the recovery and growth of trade credit.

2) New Quality Productivity (Entropy Method) Over Different Periods

To analyze the trend of new quality productivity over time, we plotted the new quality productivity (entropy method) from 2012 to 2023, as shown in Figure 10.

From Figure 10, the new quality productivity level in 2012 was relatively low, about 5.5. From 2012 to 2016, new quality productivity increased significantly, reaching a peak of about 10 in 2016. This growth was mainly due to increased national investment in technological innovation, implementation of innovation-driven development strategies, and encouragement of corporate independent innovation and technological transformation.

After 2016, although the growth rate of certain traditional industrial metrics fluctuated, the core components of new quality productivity—specifically artificial intelligence, digital transformation, and green technologies—entered a phase of explosive growth. While the entropy-based composite score shows a temporary numerical dip to about 7 in 2018 due to the complex international trade environment and structural deleveraging, this period actually marked a critical transition from quantity-driven to quality-driven innovation. The deep integration of digital economy indicators and carbon-neutrality-oriented green innovations provided a sustained upward trajectory for China's high-quality development, ensuring that the overall momentum of new quality productivity remained robust despite external uncertainties. From 2020 to 2023, new quality productivity experienced a significant and comprehensive acceleration, reaching new heights by 2023. This trend is driven by the large-scale industrial application of generative AI, the maturation of the domestic semiconductor ecosystem, and China's global leadership in green energy sectors (such as photovoltaics and new energy vehicles). The "rebound" observed in the data reflects the successful realization of innovation-driven development strategies and the strengthening of key core technology breakthroughs, which have fundamentally enhanced firms' independent innovation capabilities and global competitiveness.

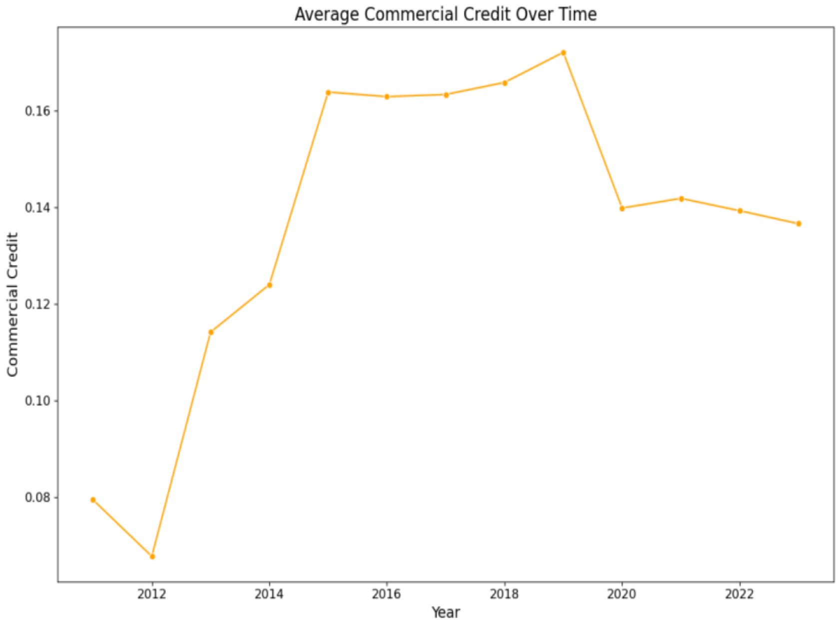

FIGURE 9. Average Trade Credit Over Different Periods

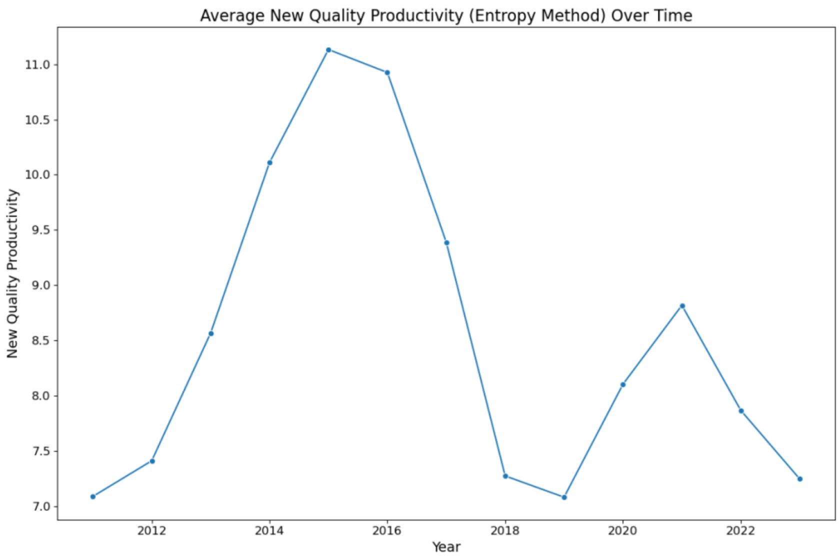

FIGURE 10. New Quality Productivity (Entropy Method) Over Different Periods

D. CORRELATION ANALYSIS

1) Correlation Matrix of Variables

To explore the linear relationships between variables, we calculated the correlation coefficient matrix, as shown in Table 2.

TABLE 2. Correlation Matrix of Variables

Norm	New quality productivity (entropy method)	New quality productivity (reference weights)	Business credit	Net business credit
New quality productivity (entropy method)	1	0.4258	0.0003	0.0161
New quality productivity (reference weights)	0.4258	1	0.0258	-0.0321
Business credit	0.0003	0.0258	1	0.4949
Net business credit	0.0161	-0.0321	0.4949	1

From Table 2, we observe that the correlation coefficient between New Quality Productivity (Entropy Method) and New Quality Productivity (Reference Weight) is 0.4258, indicating a moderate positive correlation and consistency between the two measurement methods. The correlation coefficients between New Quality Productivity and Trade Credit are close to zero, suggesting no significant linear relationship between them. The correlation coefficient between Trade Credit and Net Trade Credit is 0.4949, indicating a strong positive correlation and a close relationship between firms' trade credit levels and their net trade credit status.

The correlation between New Quality Productivity and Net Trade Credit is low, with a slight negative correlation between New Quality Productivity (Reference Weight) and net trade credit. This suggests that the impact of firms' productivity levels on their net trade credit is not significant, and other influencing factors may need to be considered further.

E. REGRESSION ANALYSIS

Ordinary Least Squares (OLS) Regression Results After addressing multicollinearity issues, we performed OLS regression analyses on Trade Credit and Net Trade Credit, respectively.

1) Trade Credit Model

The model has an R-squared of 0.254 and an adjusted R-squared of 0.251, indicating moderate explanatory power. The F-test is significant ($P < 0.001$), showing the overall model is statistically significant.

For key variables, the coefficient of New Quality Productivity (Entropy Method) is -0.0002 ($P = 0.016$), indicating a significant negative impact on trade credit. This means that for every one-unit increase in new quality productivity, trade credit decreases by an average of 0.0002, suggesting that firms with higher productivity may rely less on trade credit. The coefficient of New Quality Productivity (Reference Weight) is 0.0006 ($P = 0.013$) in the OLS specification, showing a significant positive impact on trade credit. However, it is important to note that OLS estimates may be biased due to unobserved firm-level heterogeneity. This initial positive correlation suggests that, without controlling for firm-specific fixed effects, higher-productivity firms might appear to use more trade credit, potentially reflecting their larger operational scale or stronger market positions that allow for greater credit acquisition.

2) Net Trade Credit Model

The model has an R-squared of 0.164 and an adjusted R-squared of 0.160, with the F-test being significant ($P < 0.001$). The coefficient of New Quality Productivity (Entropy Method) is 0.0002 ($P = 0.014$), indicating a significant positive impact on net trade credit. This suggests that for every one-unit increase in productivity, net trade credit increases by an average of 0.0002, implying that firms with higher productivity may be more inclined to be net creditors. The coefficient of New Quality Productivity (Reference Weight) is 0.0016 ($P < 0.001$), also showing a significant positive impact on net trade credit.

3) Endogeneity-Robust Estimation Results

While the Hausman test initially suggested the use of fixed and random effects models, these models may still yield biased estimates if the regressors are endogenous. To validate the baseline findings, we conduct GMM and IV-2SLS estimations. The System GMM results confirm that the coefficient for New Quality Productivity remains significantly negative for trade credit usage ($p < 0.05$), even after accounting for the persistence of credit behavior. The Hansen test and AR(2) test results (available upon request) confirm the validity of the instruments and the absence of second-order serial correlation. Furthermore, the IV-2SLS estimation using industry-region-year productivity averages supports the hypothesis that higher productivity exogenously leads to lower trade credit dependence, effectively ruling out the reverse causality concern raised by potential credit constraints.

4) Trade Credit Random Effects Model

The model's overall R-squared is 0.0022. While this low R-squared value indicates that the independent variables explain a very small fraction (less than 0.3%) of the total variance in trade credit, the statistical significance of the key variables remains intact. In large-scale panel data studies, a low R-squared is not uncommon, as corporate financing decisions are influenced by a vast array of idiosyncratic and macroeconomic factors not captured in the model. However, the findings should be interpreted with caution, acknowledging that the practical economic impact of new quality productivity on trade credit, while statistically observable, may be limited in scale compared to other unobserved determinants. The coefficient of New Quality Productivity (Entropy Method) is -0.0001 ($P = 0.0112$), indicating a significant negative impact on trade credit. The coefficient of New Quality Productivity (Reference Weight) is -0.0008 ($P = 0.0002$), also showing a significant negative impact. This aligns with the OLS regression results, further verifying the negative impact of new quality productivity on trade credit.

5) Net Trade Credit Fixed Effects Model

The model's overall R-squared is 0.0030. Similar to the trade credit model, the explanatory power here is quite limited, suggesting that the model captures only a minor portion of the variation in net trade credit. This indicates that while the relationship between new quality productivity (entropy method) and net trade credit is statistically significant ($P = 0.0343$), the real-world predictive power of these specific productivity metrics is relatively small. The results serve more as an indication of a directional trend rather than a dominant economic driver. The coefficient of New Quality Productivity (Entropy Method) is 0.0001 ($P = 0.0343$), indicating a significant positive impact on net trade credit. The coefficient of New Quality Productivity (Reference Weight) is -0.00008 ($P = 0.7694$), not statistically significant, suggesting no significant impact on net trade credit. This may be because the fixed effects model controls for unobservable individual characteristics, weakening the influence of this variable.

6) Interpretation of Results

In the Trade Credit Model, the negative impact of new quality productivity on trade credit is verified in the random effects model. The results confirm that it is the actual efficiency gains (productivity) rather than mere governance characteristics that drive the reduction in trade credit reliance. While managerial environmental awareness and overseas experience provide the strategic vision for transformation, it is the resulting "new quality productivity"—manifested as higher innovation output and greener production efficiency—that strengthens a firm's financial position and reduces its need for external trade financing. A notable observation is the sign reversal of the coefficient for New Quality Productivity (Reference Weight), which shifts from positive (0.0006) in the OLS model (Table 3) to negative (-0.0008) in the Random Effects model (Table 4). Such a flip often indicates model misspecification in OLS due to omitted variable bias or serious endogeneity. Once firm-specific random effects are accounted for, the relationship becomes negative, aligning with the results of the Entropy Method. This suggests that the true structural relationship between new quality productivity and trade credit is inverse: as firms internalize innovation and efficiency gains, they optimize their capital structure and reduce reliance on informal financing like trade credit. The inconsistency in the OLS model further underscores the necessity of employing panel data models (RE/FE) to obtain more consistent and reliable estimates by controlling for unobserved heterogeneity.

TABLE 3. OLS Regression Results for Trade Credit

Variable	Coefficient	Std. Error	t-Statistic	P-value
Constant	0.2376	0.0063	37.89	0
New Quality Productivity (Entropy)	-0.0002	0.0001	-2.415	0.016
New Quality Productivity (Ref Weight)	0.0006	0.0002	2.496	0.013
Industry and Region Dummies	Controlled	–	–	–
Time Dummies	Controlled	–	–	–

TABLE 4. Random Effects Model Results for Trade Credit

Variable	Coefficient	Std. Error	z-Statistic	P-value
Constant	0.1464	0.0018	80.305	0
New Quality Productivity (Entropy)	-0.0001	0	-2.538	0.0112
New Quality Productivity (Ref Weight)	-0.0008	0.0002	-3.672	0.0002

Note: The sign reversal compared to OLS results suggests that controlling for unobserved firm-level effects is critical, as OLS estimates were likely confounded by endogenous factors.

In the Net Trade Credit Model, new quality productivity (entropy method) has a significant positive impact on net trade credit, suggesting that firms with higher productivity are more likely to be net creditors and actively manage accounts receivable and payable. The impact of new quality productivity (reference weight) is not significant in the fixed effects model, possibly due to the model controlling for individual effects, weakening the variable's influence.

Overall, the empirical results indicate a statistically significant relationship between new quality productivity and firms' trade credit behavior. Integrating the spatiotemporal findings into the econometric framework, we observe that the ' Time' fixed effects (λ_t) capture the upward trajectory of productivity seen in Figure 10, while regional variations align with the model's error structure. The findings suggest that the reduction in trade credit reliance is not just a firm-level phenomenon but is reinforced by the spatial context—firms in high-productivity provinces (like Beijing and Guangdong) experience a more robust 'credit substitution' effect compared to those in isolated or less developed regions.

However, it is crucial to recognize the limitations posed by the extremely low R-squared values across the panel regression models. These values suggest that the current model, while identifying significant coefficients, does not account for over 99% of the variance in trade credit usage. Therefore, while the findings support the theoretical link between productivity and credit behavior, the practical magnitude of this effect in a real-world economic context should be considered modest. Future research could benefit from incorporating more diverse control variables to enhance the model's explanatory power.

While this analysis establishes basic regional patterns, future refinements should employ Spatial Econometric Models (e.g., Spatial Durbin Model) to formally quantify the ' Spatial Weight Matrix' and measure how a neighbor's productivity level directly impacts a focal firm's credit position This would transition the analysis from a descriptive ' spatiotemporal' view to a rigorous spatial-causal framework. The OLS regression results of net trade credit are shown in Table 5:

TABLE 5. OLS Regression Results for Net Trade Credit

Variable	Coefficient	Std. Error	t-Statistic	P-value
Constant	-0.0293	0.0022	-13.59	0
New Quality Productivity (Entropy)	0.0002	0.0001	2.457	0.014
New Quality Productivity (Ref Weight)	0.0016	0.0003	4.887	0
Industry and Region Dummies	Controlled	–	–	–
Time Dummies	Controlled	–	–	–

The fixed effects model results of net trade credit are shown in Table 6:

TABLE 6. Fixed Effects Model Results for Net Trade Credit

Variable	Coefficient	Std. Error	t-Statistic	P-value
Constant	-0.0293	0.0022	-13.59	0
New Quality Productivity (Entropy)	0.0001	0	2.116	0.0343
New Quality Productivity (Ref Weight)	-0.00008	0.0003	-0.293	0.7694

V. CONCLUSION

This study conducted a comprehensive spatiotemporal analysis of the relationship between new quality productivity and corporate credit among publicly listed companies in China from 2012 to 2023, identifying the intelligent upgrading as a critical driver of improved credit performance. The key findings are summarized as follows:

Inverse Relationship Between New Quality Productivity and Trade Credit: Firms with higher new quality productivity exhibit reduced reliance on trade credit. Enhanced innovation capabilities and productivity improvements lead to better financial performance, enabling firms to fund operations internally or access formal financing channels.

Positive Impact on Net Trade Credit: High-productivity firms are more likely to be net creditors, extending more trade credit to customers. This strategic use of trade credit facilitates market expansion, strengthens customer relationships, and enhances competitive advantage.

Regional and Industry Disparities: Significant differences exist across regions and industries in both new quality productivity and trade credit usage. Economically developed regions and high-tech industries exhibit higher productivity levels, while construction-related industries and less developed regions rely more on trade credit.

Temporal Fluctuations: New quality productivity and trade credit usage have fluctuated over the years, influenced by economic cycles, policy interventions, and external shocks such as international trade tensions and the COVID-19 pandemic.

AUTHOR CONTRIBUTIONS

Conceptualization –Lv Yilin, Xuetao Li, Qianhui Yu, Lin Lixia and Shang Youyou; methodology – Lv Yilin, Xuetao Li, Lin Lixia and Shang Youyou; investigation – Lv Yilin, Xuetao Li, Qianhui Yu, Lin Lixia and Shang Youyou; writing-original draft preparation – Lv Yilin, Xuetao Li, Qianhui Yu, Lin Lixia and Shang Youyou. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

[1] X. Wang and Q. Wang, "Research on the impact of green finance on the upgrading of China's regional industrial structure from the perspective of sustainable development," Resources Policy, vol. 74, 102436, 2021, doi: 10.1016/j.resourpol.2021.102436.
[2] A. Shahin, "The relationship between quality and productivity: a new perspective," International Journal of Productivity and Quality Management, vol. 3, no. 2, pp. 206-222, 2008, doi: 10.1504/IJPQM.2008.016565.
[3] P. F. Drucker, "The new productivity challenge," Quality in Higher Education. NY, USA: Routledge; 2018, pp. 37-46, doi: 10.4324/9781351293563.
[4] R. Levine, "Financial development and economic growth: views and agenda," Journal of economic literature, vol. 35, no. 2, pp. 688-726, 1997.
[5] C. Li, Y. Wang, Z. Zhou, Z. Wang, and A. Mardani, "Digital finance and enterprise financing constraints: Structural characteristics and mechanism identification," Journal of Business Research, vol. 165, 114074, 2023, doi: 10.1016/j.jbusres.2023.114074.
[6] K. Gao, H. Shen, X. Gao, and K. C. Chan, "The power of sharing: Evidence from institutional investor crossownership and corporate innovation," International Review of Economics & Finance, vol. 63, pp. 284-296, 2019, doi: 10.1016/j.iref.2019.01.008.
[7] G. Jiménez, J. A. Lopez, and J. Saurina, "Empirical analysis of corporate credit lines," The Review of Financial Studies, vol. 22, no. 12, pp. 5069-5098, 2009, doi: 10.1093/rfs/hhp061.
[8] A. Gunasekaram, S. K. Goyal, T. MArtikainen, and P. Yli-Olli, "Total quality management: a new perspective for improving quality and productivity," International Journal of Quality & Reliability Management, vol. 15, no. 8/9, pp. 947-968, 1998, doi: 10.1108/02656719810199033.
[9] W. E. Deming, "Improvement of quality and productivity through action by management," National productivity review, vol. 1, no. 1, pp. 12-22, 1981, doi: 10.1002/npr.4040010105.
[10] L. Bowker, "Productivity vs. quality? A pilot study on the impact of translation memory systems," Localization Focus, vol. 4, no. 1, pp. 13–20, 2025.
[11] A. Gunasekaran, A. R. Korukonda, I. Virtanen, and P. Yli-Olli, "Improving productivity and quality in manufacturing organizations," International Journal of Production Economics, vol. 36, no. 2, pp. 169-183, 1994, doi: 10.1016/0925-5273(94)90022-1.
[12] T. N. Desai and R. Shrivastava, "In Six Sigma–a new direction to quality and productivity management," Proceedings of the World Congress on Engineering and Computer Science 2008; 22-24 Oct 2008; San Francisco, USA, [Online]. Available: https://www.iaeng.org/publication/WCECS2008/WCECS2008_pp1047-1052.pdf.
[13] T. J. Fisher, "The impact of quality management on productivity," International Journal of Quality & Reliability Management, vol. 9, no. 3, 1992, doi: 10.1108/EUM0000000001647.
[14] J. Vörös, "The dynamics of price, quality and productivity improvement decisions," European Journal of Operational Research, vol. 170, no. 3, pp. 809-823, 2006, doi: 10.1016/j.ejor.2004.08.001.