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An Empirical Study on the Impact of Digital Economy Development on Industrial Structure Optimization in Northeast China

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Abstract: The clarification of how to use digital technology to accelerate the optimization of industrial structure in Northeast China will provide theoretical support for the policy proposals for the comprehensive revitalization of Northeast China and has certain reference value for other Chinese provinces and regions as well. In this article, entropy method, system GMM dynamic panel model and Robust regression model were used to quantitatively measure the panel data of the three Northeast provinces from 2013 to 2022 around the comprehensive level of digital economy development and its impact on industrial structure optimization, as well as the sub-dimensional test and spatial heterogeneity test. The results show that the driving force of digital economy has not yet been fully released, which cannot effectively promote the rationalization and upgrading of the industrial structure. To this end, the three Northeastern provinces should establish a learning mechanism, coordinate development, implement differentiated strategies, improve personnel training and development, accelerate the cultivation of digital emerging industries and the penetration and integration of industrial digitalization.

1. Introduction

The year 2023 marks the 20th anniversary of the implementation of the Northeast Revitalization Strategy, during which remarkable achievements have been made in the development of the three provinces. But for a long time, Northeast China has relied overly on heavy chemical and resource-based industries, resulting in the slow upgrading of traditional industries and the lagging development of emerging industries. The new round of scientific and technological revolution after the epidemic is bringing new opportunities for development, and the digital economy has become a strategic priority. Therefore, how the three provinces use digital technology to accelerate the intelligent transformation of traditional industries, actively support the accelerated development of emerging industries, and form an industrial pattern of multi-point support and multi-industry development as soon as possible has become a new focus that needs to be solved.

Regarding the academic research on the impact of digital economy development on the optimization of industrial structure, foreign scholars have carried out earlier but have little production. Mason. G's 1996 research showed that data and information technology could contribute to the promotion and institutional development of the food industry [1]. In 1999, Hans-Dieter Zimmermann and another scholar conducted a study on the impact of digital economy on the financial industry [2]. Later, foreign scholars paid more attention to the impact of ICT on industrial structure, such as Dewan et al. (2000), O'Mahoney et al. (2005), Lee et al. (2009) and Krogh (2012) [3-6]. In contrast, domestic scholars have a late start in their research, but their findings are more abundant. At present, their research mainly involves three aspects: influencing mechanism and pathways, and empirical analysis. In terms of influencing mechanism and pathways, some scholars believe that the digital economy has a direct impact on the optimization of industrial structure. Kang Tiexiang (2008) found that the development of digital economy could directly promote the upgrading of industrial structure through industrial integration and the birth of new industries [7], while Li Yiming (2019) believed that digital industrialization and industrial digitalization were the major driving forces [8]. Some scholars believe that digital economy has an indirect impact on industrial structure upgrading through intermediary mechanism. Laudien et al. (2019) believed that digital technology and digital commercialization activities could help improve the efficiency of service industry, thus promoting the upgrading of industrial structure [9]. In addition, scholars such as Xu Xiaohui (2022), Wang Jun, Liu Xiaofeng (2023), etc., also conducted similar research [10-11]. In terms of empirical analysis, the existing literature mostly used the intermediary effect model, panel threshold model, system GMM model, spatial Durbin model, etc., to investigate. Representatives are scholars such as Li Xiaozhong, Wu Jiaxu (2020), Cheng Guangbin and Wu Jiaqing et al. (2022), Yang Anthems and Deng Feng (2023), etc. [12-14].

This article uses entropy method, system GMM dynamic panel model and Robust regression model to quantitatively measure the panel data of the three Northeast provinces from 2013 to 2022 around the comprehensive level of digital economy development and its impact on industrial structure optimization, as well as the sub-dimensional test and spatial heterogeneity test. These fill the gaps in the empirical research on the digital economy in Northeast China in terms of time and space. Through empirical tests and exploration, the three provinces could discover the critical points to promote the optimization of industrial structure, give full play to the advantages of latecomers, and gradually narrow the development gap with the domestic-developed regions.

2. Research Design

2.1. Methodology

2.1.1. Comprehensive Evaluation Model – Entropy Method

Entropy method is a widely used multi-index objective weighting method. It determines the influence of their relative change degree on the whole system by calculating the information entropy of each index to assign relative weight value to each index. In this article, after establishing the index system of the digital economy development level, entropy method is used to assign weights to various indicators, and then the comprehensive score is obtained.

2.1.2. Setting of Empirical Models

1) System GMM dynamic panel model

GMM is a parameter estimation method based on the actual parameters of the model meeting certain moment conditions. "Dynamic panel model" is to include the lag value of the explained variable in the explanatory variable of the panel model, whose purpose is to avoid the endogeneity problem in the explanatory variable. In order to avoid the partial sample information loss and the shortcomings of weak instrumental variables brought by differential GMM, the systematic GMM estimation method proposed by Blundell and Bond is adopted in this study. In this paper, the dynamic panel model is selected as the benchmark model, which is set as follows:

$$RIS_{i,t}=\alpha_0+\alpha_1 RIS_{i,t-1}+\alpha_2 DIG_{i,t}+\sum_{m=1}^{n}\alpha_n Control_{it,m}+\mu_{1,i}+\varepsilon_{1,it} \tag{1}$$

$$AIS_{i,t}=\beta_0+\beta_1 AIS_{i,t-1}+\beta_2 DIG_{i,t}+\sum_{m=1}^{n}\beta_n Control_{it,m}+\mu_{2,i}+\varepsilon_{2,it} \tag{2}$$

Where $RIS_{i,t}$, $AIS_{i,t}$ and $DIG_{i,t}$ respectively represent the rationalization level of industrial structure, the advanced level of industrial structure and the development level of digital economy of a certain region of i in the year of t. DGD, IDG, DGI and DGB are the four decomposition items of DI, respectively represent digital driving, industrial digitalization, digital industrialization, and digital base. $Control_{it,m}$ represents different control variables, mainly including STEC, HUM, CNS, GOV, OPN, which respectively represents the level of scientific and technological innovation, the advanced level of human capital, the advanced level of consumption structure, the degree of government support and the level of opening up. μ_i is the unmeasurable regional individual effect, ε_{it} is the disturbance term, α and β are the parameters to be estimated for each model.

2) Robust regression model (M estimation method)

If there are outliers in the data during linear regression analysis, the conclusion obtained by the commonly used OLS regression estimation method may be biased, and Robust regression is required in this case. In this article, where $RIS_{i,t}$ and $AIS_{i,t}$ represent the dependent variable, $DIG_{i,t}$represents the core independent variable, and $Control_{it,m}$ represents various control variables, the multiple linear regression model are as follows:

$$RIS_{i,t}=\alpha_0+\alpha_1 DIG_{i,t}+\sum_{m=1}^{n}\alpha_n Control_{it,m}+\varepsilon_{1,it} \tag{3}$$

$$AIS_{i,t}=\beta_0+\beta_1 DIG_{i,t}+\sum_{m=1}^{n}\beta_n Control_{it,m}+\varepsilon_{2,it} \tag{4}$$

Where α_0 and β_0 are the population intercept, and α_1, α_n, β_1, β_n respectively are the population partial regression coefficients corresponding to each independent variable, ε is the random error. The partial regression coefficient represents the average change of the dependent variable caused by each change of one unit of measurement of the independent variable when other independent variables are fixed.

2.2. Variable Description and Data Sources

2.2.1. Core Explanatory Variables

The development levels of digital economy in the three Northeast provinces are the core explanatory variables and are denoted as DIG. According to Statistical Classification of Digital Economy and Its Core Industries (2021) by the National Bureau of Statistics of China, digital economy has two parts: the core industry (i.e., digital industrialization) and the digital efficiency improvement industry (i.e., industrial digitalization). Based on this classification, this paper combs other scholars' studies on the indicator system of the development level of digital economy and builds an index system including 4 primary indexes and 43 secondary indicators, including digital base (12), digital industrialization (16), and digital driving (5), according to the relevant principles of indicator selection. In the constructed index system, different indicators have different impacts on the development level of digital economy. In order to objectively and accurately empower each indicator, this article adopts the entropy method mentioned above, assigns weight to various indicators, and then obtains the comprehensive score.

2.2.2. Core Explained Variables

The fundamental criterion of industrial structure optimization is that it must be conducive to the sustained, healthy and stable development of regional economy, including rationalization and upgrading of industrial structure. This article will draw on the practice of scholars such as Zhang Zengchen (2018) and set the rationalization level (RIS) and the advanced level (AIS) of the industrial structure in the three provinces as the core explained variables [15]. Theil Index (TL) is introduced to measure the rationalization level of industrial structure; "tertiary industry added value/secondary industry added value" is used to measure the upgrading level of industrial structure.

2.2.3. Control Variables

The optimization of industrial structure will be affected by multiple factors. In order to improve the accuracy and reliability of empirical tests, this article selected the level of scientific and technological innovation, the advanced level of consumption structure, the advanced level of human capital, the level of government support and the level of opening up as control variables, and recorded as STEC, CNS, HUM, GOV, OPN respectively. The specific measurement methods are shown in Table 1:

Table 1. Control variables and measurement methods.

Control Variable	**Measurement Method**
STEC	Ln (the number of domestic valid patents)
CNS	Ln (total consumer goods)
HUM	Ln (the number of students graduating from college or above)
GOV	local fiscal expenditure/GDP
OPN	Ln (amount of foreign direct investment)

2.2.4. Data Sources

In view of the availability and completeness of the data, the panel data of the three provinces from 2013 to 2022 are selected as the research object. Among them, the Digital Financial Inclusion index comes from the Digital Finance Research Center of Peking University, while the other data are from the National Statistical Yearbook, Jilin Statistical Yearbook, Liaoning Statistical Yearbook, Heilongjiang Statistical Yearbook, Science and Technology Statistical Yearbook, and High-tech Industry Statistical Yearbook. For individual missing data, the mean value method was used to fill in the data by referring to existing research. To alleviate the impact of heteroscedasticity, logarithmic processing is carried out for variables with large numbers.

3. Results

3.1. Evaluation of the Digital Economy Development Level

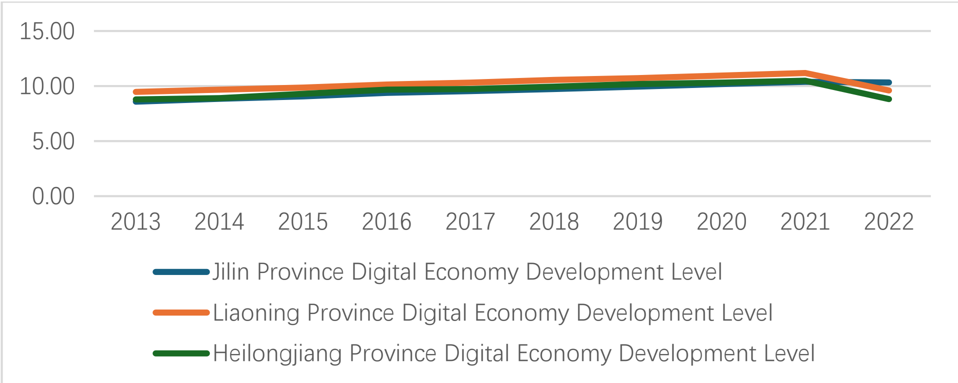

Figure 1. Development level of digital economy in Northeastern China (2013-2022).

As can be seen from Figure 1, except for the worst period of the epidemic in 2022, the digital economy of Northeast China had achieved certain development, but the gap among the three provinces was obvious, which indicates the development of digital economy in the three provinces is uneven and seriously differentiated. Among them, Liaoning Province takes the lead, and its comprehensive index is significantly better than that of Heilongjiang and Jilin provinces. And meanwhile, Heilongjiang Province has a slightly higher level than Jilin Province.

Quantitative analysis of the fractal dimension shows that the development of four subsystems in Liaoning Province is relatively balanced, and the overall level is better than that of the other two provinces. Even so, a few aspects have gradually declined in ranking lately and lost their superiority. In the meantime, Heilongjiang and Jilin provinces lag in the four sub-systems, especially in the aspects of digital driving and industrial digitalization. However, for the past few years, the two provinces have gradually become more digital-conscious, increased investment and support in digital infrastructure, scientific and technological innovation, and talent education, and made impressive achievements.

3.2. Unit Root Test

This paper first conducts unit root tests on each variable to avoid pseudo-regression. The result shows that the first-order difference of each variable passes the HT test at the significance level of 1%, which indicates that each variable has a first-order single integral relationship, and the data is stable.

3.3. System GMM Dynamic Panel Analysis

All the following models have passed the Hansen over-recognition test and the non-autocorrelation AR test of the perturbation term, indicating that the models are well constructed and can be used for analysis.

3.3.1. Comprehensive analysis of Northeast China

According to Table 2, the rationalization of industrial structure in Northeast China mainly comes from the first-order lag of the explained variables, government support, and opening up. Among them, the regression value of the first-order lag term of the explained variables is positive and significant, indicating that the rationalization level of the explained variables of the industrial structure of the three provinces is dynamic in terms of time trend, which confirms that the setting of the dynamic panel model is reasonable. On the other hand, it reflects that there is a certain inertia and continuity in the rationalization level of the industrial structure of the three provinces. The regression coefficient of digital economy development level at the significance level of 1% is -0.192, which indicates that it has a significant inhibitory effect on the rationalization of industrial structure. The possible explanation is that the three provinces lack the common top-level design and strategic deployment for the coordinated development of regional economy, coupled with the internal administrative barriers, institutional barriers, imperfect market regulation mechanism, and the large differences in industrial structure and technology, which makes it difficult for the digital economy development in the three provinces to play a significant role in promoting the rationalization of industrial structure.

Table 2. GMM dynamic panel model results.

Explained Variable = RIS		**Explained Variable = AIS**	
Item	Regression Coefficient	Item	Regression Coefficient
L1. RIS	0.720 * *	L1. AIS	0.532 * *
DIG	-0.192 * *	DIG	0.138 *
STEC	0.007	STEC	-0.052
CNS	0.008	CNS	0.033
HUM	-0.024	HUM	0.235
GOV	0.002 * *	GOV	0.019 * *
OPN	0.008 *	OPN	-0.027 * *
* $p<0.05$ ** $p<0.01$			

Table 2 demonstrates that the upgrading of industrial structure in Northeast China is mainly influenced by the first-order lag of the explained variables, digital economy development, and government support. The regression value of the first-order lag term of the explained variable is positive and significant, which indicates that the explained variable of the advanced level of industrial structure also has a certain inertia and persistence in the time series. However, the degree of opening up has a reverse effect on it, which might be explained by the fact that foreign investment in the three provinces is mainly in the secondary industry, and its purpose is to transfer excess domestic production capacity, find cheap raw materials, labor resources and a huge consumer market. As a consequence, the technological spillover effect is very limited, which is rather difficult to improve the level of industrial structure upgrading.

3.3.2. Dimensional analysis of Northeast China

As shown in Table 3, the digital base can improve the upgrading level of industrial structure in Northeast China at the significant level of 5%, and the regression coefficient is 0.417, which indicates that the influence is limited, but has no significant impact on the rationalization of industrial structure. As an important old industrial base, traditional industries such as heavy industries started early and have a large scale, which is a good industrial carrier for natural integration with the digital economy, and appropriate integration can effectively promote the upgrading of industrial structure. However, the linkage between various levels of the industry is not sufficient, and the docking efficiency and strength of various levels of the industrial chain are insufficient, which inhibits the rationalization of the industrial structure. Furthermore, the investment in digital infrastructure in Northeast China is uneven and at a low and medium level.

Table 3 shows that digital driving plays a significant role in the two explained variables at the 1% level, but in opposite directions. The reasons may be the backward industrial development, the inability of a large number of workers in traditional industries to adapt to the development of the digital economy, the behindhand development in vocational education, the lack of efforts in training high-tech industry workers, and the serious loss of high-quality professionals in Northeast China.

Table 3. GMM dynamic panel model results of the dimensional analysis.

Explained variable = RIS		Explained variable = AIS	
Item	**Regression Coefficient**	**Item**	**Regression Coefficient**
L1. RIS	1.012 * *	L1. AIS	0.313 * *
STEC	0.075 * *	STEC	-0.107
CNS	0.079 * *	CNS	0.029
HUM	0.207 * *	HUM	1.298 * *
GOV	0.015 * *	GOV	-0.003
OPN	0.016 * *	OPN	-0.055 * *
DGD	0.189 * *	DGD	-0.850 * *
IDG	-0.293 * *	IDG	0.267 * *
DGI	-0.034	DGI	0.022
DGB	-0.026	DGB	0.417 *
* p<0.05 ** p<0.01			

As can be seen in Table 3, at 1% level, industrial digitalization can significantly improve the upgrading level but has a significant inhibitory effect on the rationalization. In recent years, on the road to high-quality development in the three provinces, traditional industrial problems have become increasingly prominent, such as single structure, traditional products accounting for the majority, and “original brand” and “initial brand” products constituting the majority. In particular, the “time-honored brands” that account for a large proportion have a low level of intelligence, weak industrial basic capabilities, low industrialization rate of innovation achievements, and new growth points have not yet been systematically formed, all of which seriously inhibit the rationalization process.

According to Table 3, digital industrialization has no significant impact on the two explained variables. At present, the digital economy in the three provinces is dominated by e-commerce. There is no doubt that the development of e-commerce has an important role in promoting the economy and can drive the increase of employment. However, the development of e-commerce cannot promote the fundamental transformation of economic development model, drive the development of core technologies, and give full play to the effect of the digital economy in promoting industrial transformation and upgrading.

3.4. Robust Regression Analysis

3.4.1. Comprehensive analysis by province

Taking the rationalization level of industrial structure in Northeast provinces as the dependent variable, Robust regression analysis is performed, and the results are as follows.

Table 4. Robust regression analysis results of industrial structure rationalization level by province.

Item	Jilin Province RIS regression coefficient	Liaoning Province RIS regression coefficient	Heilongjiang Province RIS regression coefficient
Constant	-2.028	-3.056 * *	1.450 * *
DIG	0.047	0.008 * *	-0.034 * *
STEC	0.005	0.002	-0.066 * *
CNS	0.151 * *	0.076 * *	0.036 * *
HUM	0.319	0.169 * *	-0.044 * *
GOV	-0.018 *	0.004 * *	-0.006 * *
OPN	-0.178 *	0.013 * *	0.020 * *
R^2	0.99	0.865	0.884
Adjust R^2	0.971	0.596	0.653
* p<0.05 ** p<0.01			

From Table 4, digital economy has no significant impact on the rationalization of industrial structure in Jilin Province. The driving force of the rationalization mainly comes from the upgrading of consumption structure, while the government support and the level of opening up constitute the main obstacles. In Liaoning Province, digital economy development will have a significant positive impact on the rationalization level of industrial structure, and the value of 0.008 regression coefficient indicates that the promotion effect is very limited. Among the other variables, the regression coefficients are all positive except for the insignificant effect of scientific and technological innovation, which indicates that the rationalization of industrial structure is the result of the comprehensive effect of multiple factors. In Heilongjiang Province, the rationalization of industrial structure mainly stems from the upgrading of consumption structure and the pull of opening up, while the development of digital economy, scientific and technological innovation, the advanced level of human capital and government support all have significant restricting effects on the rationalization level.

Taking the advanced level of industrial structure in Northeast provinces as the dependent variable, Robust regression analysis is performed, and the results are as follows.

Table 5. Robust regression analysis results of industrial structure advanced level by province.

Item	Jilin Province AIS regression coefficient	Liaoning Province AIS regression coefficient	Heilongjiang Province AIS regression coefficient
Constant	3.410	-27.855	-36.177 *
DIG	0.298	0.281	0.424
STEC	-0.255	-0.425	-0.381
CNS	-0.386	-0.259	0.950 * *
HUM	-0.772	2.829	2.286
GOV	0.064	0.018	0.026
OPN	0.532	-0.183 *	0.120
R^2	0.98	0.946	0.978
Adjust R^2	0.941	0.839	0.934
* p<0.05 ** p<0.01			

Exhibited in the Table 5, the development of digital economy has no significant impact on the advanced level of industrial structure in the three provinces, which indicates that the development of digital economy is seriously inconsistent with the upgrading level of industrial structure.

3.4.2. Dimensional analysis by province

This study then takes the four decomposition variables of the digital economy development index respectively (digital driving, industrial digitalization, digital industrialization and digital base) as independent variables, and the rationalization level and the advanced level of industrial structure in the three provinces respectively as dependent variables to perform Robust regression analysis. Empirical results illustrate that in Jilin Province, the rationalization of industrial structure is primarily attributed to digital driving and digital base, while the upgrading of industrial structure is largely thanks to digital driving, digital industrialization and digital base. In Liaoning Province, the rationalization of industrial structure is mostly due to digital driving, while the upgrading of industrial structure mainly results from digital industrialization and digital base. In Heilongjiang Province, digital driving, industrial digitalization and digital industrialization will have obvious inhibitory effect on the rationalization of industrial structure. The upgrading of industrial structure mainly comes from digital driving and digital base. Therefore, it is concluded that digital construction and government support constitute the main reasons of the optimization of industrial structure in Northeast China. However, digital industrialization and industrial digitalization are relatively weak and have not played a strong role in promoting it.

3.5. Robustness Test Based on Bidirectional Shrinking Tail

To further verify whether the empirical results are robust, the robustness test method of 5% bidirectional tail shrinkage processing on the original data is adopted in this article. The results show that the conclusions after tailing reduction of the original data are basically consistent with the previous ones, which verifies the robustness of the above conclusions.

4. Conclusions and Recommendations

Northeastern China started late in the development of digital economy, with weak innovation capacity, low overall level, slow and uneven development, so its driving force has not been fully released and can't effectively promote the rationalization and upgrading of industrial structure. From a dimensional perspective, government support, industrial environment improvement and digital infrastructure play a key role in the optimization of industrial structure, while digital industrialization and industrial digitalization have not been positively promoted, and some even reversely inhibited. From a geographical perspective, Liaoning Province is better than the other two provinces, whose development level of digital economy can adapt to the rationalization of industrial structure. In other aspects, the three provinces have so far fallen behind and cannot meet the needs of optimizing industrial structure.

Based on the above conclusions, this article makes the following recommendations: (1) Establish a learning mechanism. Externally, Northeastern China should learn from the regions and provinces with advanced digital economy development in China; Internally, the two provinces of Heilongjiang and Jilin should learn from Liaoning Province. Through learning, they can gain experience and achieve the goal of rapidly improving the development level of digital economy and optimizing industrial structure. (2) Coordinate development of digital economy to create a spatial spillover effect. When formulating digital economy policies, the three provinces should, on the one hand, fully assess its possible impact on the economic development of the province and the entire Northeast region, and on the other hand, strengthen communication and coordination to form linkage, so that policies can echo each other, generate synergy, and achieve a win-win-win pattern. (3) Implement differentiated strategies of digital economy development. The three provinces should closely link with the actual development of digital economy in their own regions, formulate digital economy and industrial development policies in light of their own advantages, characteristics and shortcomings, and form differentiated core competitiveness. (4) Perfect talent training and development mechanisms. The three provinces should attach importance to the cultivation, reserve and introduction of digital talents. On the one hand, they should retain local talents through stable, coherent and generous policy subsidies and introduce high-end digital technical talents from provinces with developed digital economy, so that more and more professional digital talents and teams can participate in the digital construction of local key fields. On the other hand, by promoting in-depth cooperation among universities, research institutes and enterprises, the three provinces can cultivate exclusive digital talents and teams. (5) Accelerate the cultivation of digital industries. The three provinces should focus on promoting the rapid development of e-commerce, because they are rich in special agricultural products, industrial products and cultural and tourism products. The development of e-commerce can promote economic growth, improve the efficiency of factor flow, and cultivate soil for the comprehensive development of digital industry. (6) Accelerate the penetration and integration of digital industries. In agriculture, the three provinces should improve their corresponding digital supporting facilities to promote the development of digital agriculture. In terms of industry, intelligent manufacturing should be regarded as the core technology of industrial digitalization, and enterprises should make full use of the new generation of information technology to enable the upgrading of traditional advantageous industries. In the service sector, they will vigorously develop smart tourism, smart shopping malls and smart logistics, widely apply information technology to these industries to create smart service systems.

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