Research on the Influence of Digital Economy Development on China's Inter-provincial Path Dependence Effect

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Abstract

With the rise of the Internet industry, the digital economy has developed rapidly, and the high-quality economic development of various provinces and cities in China has also benefited a lot. Based on the comprehensive development of the digital economy in various provinces and cities and the degree of inter-provincial path dependence, this paper calculates the path dependence effect index based on the development strategy selection index and spatial adjacency matrix, calculates the evaluation index of the digital economy by entropy method, and finally explores the influence of the former on the latter by using the fixed effect model. The conclusions are as follows: Firstly, the development paths of various provinces and cities have changed many times in recent years, and the degree of path dependence has also changed greatly. Secondly, according to the development level of the digital economy, the provinces and cities in China are divided into three levels: advanced, intermediate, and low. The provinces and cities with the highest level of the digital economy are concentrated in the eastern region and the cities with intermediate digital economy-level account for the most significant proportion. Finally, the digital economy can improve the solidified state of the regional economy and promote the regional economic structure upgrade and benign development by promoting the construction of new development models and new formats to break through the path dependence lock.

Keywords*-Digital economy; Path dependence; High-quality development of regional economy*

1. Introduction

The problem of uneven regional economic development is widespread, related to the dependence on the local economic development model. This path dependence comes from the influence of neighbouring provinces and cities in the same direction and from the influence of the previous local development process locked in a specific solidified mode by the vested marginal return. For a long time, this path-dependent locking will significantly limit the industrial structure transformation and economic structure upgrading of provinces and cities, which is not conducive to the local breakthrough of inefficient solidified development mode. However, with the rapid development of the Internet, the digital economy is increasingly taking part in the national economy as a factor of great vitality, which may play a particular role in alleviating the economic rigidity and downward pressure, stimulating the new vitality of natural industries and optimizing the economic structure. Based on this, it is of practical significance to study the influence of the digital economy on the breakthrough of path dependence.

2. Literature Review

The concept of path dependence originated from the field of biology. Waddington(1957) discovered that there were non-overlapping and interfering evolutionary paths in biological gene transmission when studying species evolution, and then it was gradually introduced into the field of social science.

Many scholars have generally found that path dependence exists in economics. Paul David (1985) [1] discovered this path "locking" phenomenon by studying the QWERTY keyboard. Subsequently, W.Brain Arthur(1989)[2] studied the phenomenon of path dependence in economics for the first time. When an economy has accepted a specific development track in the early stage, it is likely to continue the development of the track in the later stage due to interest relations and externalities. North(2008)[3] extended technological

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change to the field of institutional change for the first time and found that if a particular development track is inefficient, it is difficult for the economies that have continued the track for many years to get rid of this development path, or even fall into a locked state where it is difficult to achieve structural transformation. Wu Jinglian (1995)[4] also believes that the original development path will continue in institutional change due to the influence of silent cost and informal vested interests. Zhang Shengling (2016)[5] found path dependence in the development of resource-based cities and thought it was challenging to change this locked state through the automatic adjustment of the market. Talebzadehhosseini Seyyedmilad; Garibay Ivan(2022)[6] explored the influence of path dependence on green economic growth and confirmed the existence of path dependence effect in the field of green economic growth. Path dependence will lead to severe problems such as insufficient endogenous motivation and structural unemployment in the development of provinces and cities. Therefore, it is urgent to find ways to break the dilemma of path dependence.

The digital economy is a dynamic economic form. The vigorous development of the digital economy in a region may improve the dependence on a local economic development path. The digital economy originated from the information economy and is the product of the development of the Internet economy. The narrow digital economy only refers to the information and communication industry, while the broad digital economy is defined as a new economic form (Colin Thirtle, 1998)[7]. The current research status of the digital economy is as follows: First, the digital economy is experiencing a stage of rapid development. Zhang Xinhong (2016)[8] believes that China's digital economy is achieving a leap-forward development with the deepening of information infrastructure construction. Second, the development of the digital economy is conducive to the new vitality of the real economy. Zhan Ning and Ouyang Yongfu (2018)[9] found that the digital economy can promote the emergence of new formats and business models and greatly promote the development of traditional industries. Zhao Xisan (2017)[10] found that the digital economy has contributed to innovation-driven development and supply-side structural reform. Yu Zhe (2018)[11] thinks that the digital economy is an important driving force in promoting the transformation of an economic model. By deepening the digitalization and informatization of the real economy, it is conducive to improving the core competitiveness of real enterprises. Third, the development of the digital economy can reform the economic structure and promote the transformation and upgrading of the economic development model and system. Yang Xinming (2017)[12] found that the digital economy can realize the zero-contact transaction mode, which promotes the conversion of market transaction structure and provides new opportunities for regional institutional innovation. Wang Weiling's (2019)[13] Research holds that the digital economy is new kinetic energy to promote high-quality economic development, and the digital economy will become an essential trend in future economic model development.

The innovations of this paper are as follows: Firstly, the path dependence effect index of each province and city is calculated by combining the actual development strategy selection index and spatial adjacency matrix of each province and city, the provinces and cities with different levels of path dependence are divided, and the overall change of path transformation and path dependence of each province and city is analyzed. Secondly, the entropy weight method constructs an evaluation index of the digital economy covering five dimensions, and three digital economy cities are divided into high, middle and low levels according to the evaluation index. Thirdly, this paper combines the development of the digital economy with the path dependence effect for the first time and explores the influence of the former on the latter, which has practical significance.

The data mainly comes from the National Bureau of Statistics, China Science and Technology Statistical Yearbook, provincial statistical yearbooks and Peking University Digital inclusive finance Index.

3. Measurement and Verification

3.1. Variable measurement and descriptive statistics

3.1.1. Path-dependent effect index measurement

3.1.1.1. Measurement method of path dependence effect

Referring to Lin Yifu (2002)[14], which measures the deviation degree between regional economic development and comparative advantageTCL, this paper constructs the strategic choice index of the actual development of provinces and cities TCL', which is measured by the ratio of actual industrial capital-labour ratio to total economic capital-labour ratio of provinces and cities.

$$TCL'_{it} = \frac{(TIOV_{it} - ILF_{it})}{(GDP_{it} - TRLF_{it})} \quad (1)$$

Among them, TIOV is the total industrial output value, ILF is the number of industrial workers, and GDP and TRLF are the total regional output value and total labour force. Based on the above indicators, the actual development strategy index TCL' in the first T period of provinces and cities is constructed to measure the combination degree of local factor endowments with comparative advantage industries. The larger TCL' is, the greater the deviation of the factor endowments of provinces and cities from their industries with comparative advantages. When the labour-intensive industries in a province shrink, the region's labour absorption capacity will decline; However, the development of local capital-intensive industries is good, and the total industrial output value will rise, which will lead to the molecule becoming smaller. Thus TCL' will become more prominent.

The measurement of the path dependence index is closely related to the change rate of TCL', and it is also affected by the degree of adjacency and development between provinces and cities [5]. The province's path dependence effect is reflected in two aspects. On the one hand, the development degree of this province will be affected by the development degree of this province in previous years. When a province or city has a path dependence phenomenon, the TCL' index of this period will be larger than that of the previous period, and the change rate R_{it} of TCL' index of the province or city that is more affected by the path dependence effect of the previous period will be more significant.

$$R_{it} = \frac{(TCL'_{it} - TCL'_{i,t-1})}{TCL'_{i,t-1}} \tag{2}$$

On the other hand, the regional development of a province or city will be significantly influenced by neighbouring provinces' development modes and levels. The changes in industrial structure, consumption demand structure and financial fluctuation in a province and city often produce spatial externalities, which radiate to surrounding provinces and cities. Adjacent cities receive external impacts from all sides, and their economic indicators will change in the same direction to a certain extent.

Based on the division of administrative regions in China in 2008, this paper establishes the spatial adjacency matrix $W_{0\text{-}1}$ of 30 provinces and cities in China (except Tibet). In $W_{0\text{-}1}$, the spatial weight coefficient w of two adjacent provinces and cities is set to 1, and the spatial weight coefficient w of the same province and two non-adjacent provinces and cities is set to 0. If there are n provinces and cities, the interaction term α_{it} of the change rate of the actual development strategy choice index TCL' of a province i and its neighbouring province j is

$$\alpha_{it} = \sum_{i,j=1}^{n} W_{ij} R_{jt} \tag{3}$$

The calculation formula of the t-period α_{it} matrix is

$$\begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1t} \\ \alpha_{21} & \ddots & \alpha \\ \vdots & \alpha_{it} & \vdots \\ \alpha_{n1} & \cdots & \alpha_{nt} \end{bmatrix} = \begin{bmatrix} W_{11} & \cdots & W_{1n} \\ W_{21} & \ddots & W_{2n} \\ \vdots & W_{ij} & \vdots \\ W_{n1} & \cdots & W_{nn} \end{bmatrix} \times \begin{bmatrix} R_{11} & \cdots & R_{1t} \\ R_{21} & \ddots & R_{2t} \\ \vdots & R_{jt} & \vdots \\ R_{n1} & \cdots & R_{nt} \end{bmatrix} \tag{4}$$

Therefore, the measurement of path dependence effect index PDI_{it} is as follows:

$$PDI_{it} = R_{it} - \frac{\sum_{i,j=1}^{n} W_{ij} R_{jt}}{\sum_{i,j=1}^{n} W_{ij}} \tag{5}$$

3.1.1.2. Measurement result of path dependence effect index

The higher the PDI is, the more serious the path dependence degree of provinces and cities is. According to the path dependence degree of provinces and cities are shown in Table 1, it can be roughly divided into three levels: high (PDI≥0.03), medium (0 ≤ PDI < 0.03) and low (PDI < 0). As shown in Table 1, the provinces and cities with low path dependence levels are the most, followed by the provinces and cities with medium path dependence levels. There are six provinces and cities with severe path dependence, including Shanghai and Guangdong.

TABLE 1. AVERAGE PATH DEPENDENCE EFFECT INDEX OF PROVINCES AND CITIES FROM 2011 TO 2019

Provinces and cities with high path dependence index	Shanghai(0.050) Tianjin(0.043) Gansu(0.032)	Liaoning (0.043) Guangdong(0.035) Shandong(0.031)
Provinces and cities with medium path dependence index	Shanxi(0.018) Sichuan(0.016) Xinjiang(0.007) Fujian(0.006) Heilongjiang(0.003)	Guizhou(0.016) Hubei(0.012) Jiangsu(0.006) Guangxi(0.005) Ningxia(0.000)
Provinces and cities with low path dependence index	Shaanxi(-0.009) Zhejiang(-0.012) Jilin(-0.013) Hunan(-0.013) Henan(-0.016) Hainan(-0.022) Yunnan(-0.094)	Neimenggu(-0.009) Jiangxi(-0.012) Anhui(-0.013) Chongqing(-0.015) Beijing(-0.020) Qinghai(-0.025) Hebei(-0.212)

In order to understand the change of path dependence direction of provinces and cities, this paper calculates the path change index CH of each province and city.

$$CH_{it} = TCL'_{t} - TCL'_{t-1} \tag{6}$$

Based on the path dependence effect index and path transition index of 30 provinces and cities in China from 2011 to 2019, the changing trend of path dependence is obtained by analyzing each province and city.

As shown in Figure 1, in 2011, the development paths of provinces and cities were scattered, and only a few provinces and cities changed their paths. In 2012, the state introduced the policy of stimulating the economy, and the central bank released funds through reverse repurchase implemented railway reform and created the economic comprehensive reform pilot zone, which significantly promoted economic vitality. The development paths of most provinces and cities have changed, and the lock-in of path dependence effect has eased. In 2014, there was a breakthrough in the recovery of the real estate market and the development of e-commerce transactions. China even signed free trade agreements with Australia and South Korea, which significantly promoted the development of foreign trade and provided opportunities for the strategic transformation of various provinces and cities. At the same time, the falling CPI index and the low innovation also indicate the coexistence of crises. The above phenomenon has prompted many provinces and cities to change their development direction and seek new development paths, but their path dependence has not changed much. In 2016, the development paths of various provinces and cities did not show the same trend, and a small number of provinces and cities increased their pace of path transformation, deepening their path dependence.

As shown in Figure 2, in 2018, due to the slowdown in economic growth, the downward pressure, the decline in consumer demand and the slowdown in investment growth in fixed assets, about half of the provinces and cities chose to change their development paths, and some provinces and cities became more dependent on their paths. In 2019, major regional plans landed one after another, which promoted regional coordination and high-quality development. At the same time, the expansion of the free trade zone and the 5G market also created favourable development conditions for various provinces and cities, and many provinces and cities improved their path dependence locking. However, 2019 was also a raging year in novel coronavirus, with great changes in industrial form, and most provinces and cities chose to keep the original development path.

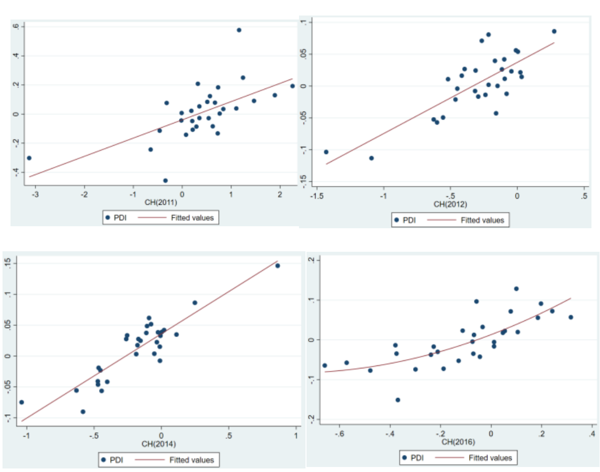

Figure 1. Path Transformation in 2011, 2012, 2014 and 2016-Scatter Diagram of Path Dependence Effect

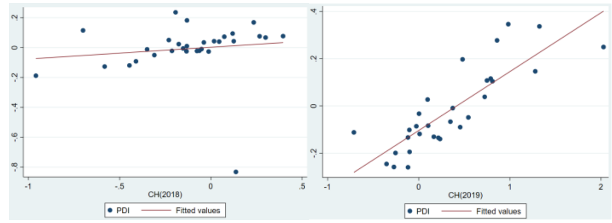

Figure 2. Path Transformation in 2018 and 2019-Scatter Diagram of Path Dependence Effect

3.1.2. Measurement of digital economic development degree

3.1.2.1. Calculation method of digital economic evaluation index

This paper refers to the comprehensive development index of digital economy constructed by Zhao Tao (2020)[15] and the measurement system of the digital economy index constructed by Liu Jun (2020)[16], a digital economy evaluation index with five dimensions, such as information development degree, internet development degree, digital transaction degree, enterprise digitalization degree and digital inclusive finance degree, is constructed as shown in Table 2.

In this paper, the index system is constructed by the entropy weight method, and the index data need to be normalized. The treatment method for positive indicators is:

$$\beta_{it} = \frac{\alpha_{it} - MIN\alpha_i}{MAX\alpha_i - MIN\alpha_i} \tag{7}$$

The treatment method for negative indicators is as follows:

$$\beta_{it} = \frac{MAX\alpha_i - \alpha_{it}}{MAX\alpha_i - MIN\alpha_i} \tag{8}$$

Among them, $MAX\alpha_i$ and $MIN\alpha_i$ are the maximum and minimum values of all provinces and cities in all years, respectively, and β_{it} is the normalized index. The index attributes of secondary indicators of the digital economic evaluation index are all positive, indicating that a single secondary indicator changes in the same direction as the primary indicator. The bigger the secondary indicator, the more outstanding its contribution to the primary indicator.

The weight of the ith province and city in the t year can be expressed by θ_{it}:

$$\theta_{it} = \frac{\alpha_{it}'}{\sum_{t=1}^{n} \alpha_{it}'} \tag{9}$$

Then, calculate the information entropy ($0 \leq e_i \leq 1$) as:

$$e_i = -\frac{1}{\ln n} \sum_{t=1}^{n} (\theta_{it} - \ln \theta_{it}) \tag{10}$$

The redundancy d_i of information entropy can be expressed by $d_i = 1 - e_i$, and the index weight calculated according to the redundancy of information entropy is:

$$\gamma_i = \frac{d_i}{\sum_{t=1}^{n} d_i} \quad (11)$$

The calculation results of each index weight are shown in Table 2.

TABLE 2. CONSTRUCTION OF DIGITAL ECONOMIC EVALUATION INDEX

Primary index	Secondary index	weight	Measurement method	Index attribute
Digital economic evaluation index(DEE)	Degree of informatization development	0.080	Number of informatization employees per hundred people	Positive
	Internet development degree	0.143	Proportion of broadband and mobile internet population	Positive
	Digital transaction degree	0.298	Proportion of online sales business of enterprises	Positive
	Enterprise digitalization degree	0.074	Number of enterprises using websites/computers	Positive
	Digital inclusive finance degree	0.406	Peking University Digital inclusive finance Index	Positive

3.1.2.2. Calculation results of digital economic evaluation index

This paper calculates the national digital economy evaluation index from 2011 to 2019, as shown in Figure 3. As shown in Figure 3, the development level of China's overall digital economy showed an upward trend from 2011 to 2019. From 2011 to 2015, the growth rate of the digital economy gradually slowed down, and in 2015, the growth rate even approached zero, which kept a steady high growth rate after exceeding the turning point of 2016.

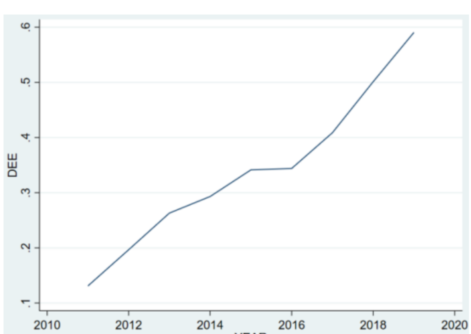

Figure 3. National Digital Economy Evaluation Index from 2011 to 2019

According to the evaluation index of the digital economy of each province, this paper divides each province into three levels: advanced digital economy province, intermediate digital economy province and low digital economy province. As shown in Table 3, Beijing, Shanghai, Zhejiang and Guangdong are classified as advanced digital economy provinces and cities, and their digital economy evaluation indexes are all greater than 0.4. The number of provinces and cities with a digital economy evaluation index between 0.3 and 0.4 is the highest, and 19 provinces and cities are classified as intermediate digital economy provinces and cities. In addition, the digital development level of seven provinces and cities is low, and the digital economy development level of most low-level digital economy provinces and cities is less than half that of high-level digital economy provinces and cities.

TABLE 3. DIGITAL ECONOMY EVALUATION INDEX OF PROVINCES AND CITIES

Advanced digital economy provinces and cities	Beijing(0.575) Zhejiang(0.428)	Shanghai(0.480) Guangdong(0.422)
Intermediate digital economy provinces and cities	Fujian(0.385) Tianjin(0.371) Hainan(0.347) Neimenggu(0.330) Hubei(0.327) Shangdong(0.320) Jilin(0.316) Shanxi(0.312) Xinjiang(0.305) Anhui(0.301)	Jiangsu(0.379) Liaoning(0.349) Shaanxi(0.344) Chongqing(0.329) Ningxia(0.325) Qinghai(0.316) Sichuan(0.313) Hebei(0.305) Heilongjiang(0.301)
Low-level digital economy provinces and cities	Yunnan(0.298) Guizhou(0.295) Jiangxi(0.292) Gansu(0.286)	Guangxi(0.296) Hunan(0.292) Henan(0.291)

3.1.3. Control variable measurement

The selection of control variables mainly refers to five aspects: the development level of each province, the regional industrial structure, the degree of education and science and technology development, the structure of foreign trade and consumer demand, capital deepening and economic fluctuation. The specific indicators are shown in Table 4, where n is the observed number.

3.1.3.1. Regional development level

The regional development level is measured by the per capita GDP (RGDPPC), obtained by dividing the GDP by the resident population and can effectively measure the regional macroeconomic operation.

3.1.3.2. Regional industrial structure

The level of regional industrial structure (RISL) is measured by the ratio of the output value of the tertiary industry to the output value of the secondary industry. The development of the tertiary industry is usually faster than that of the secondary industry. This ratio can be used to measure the development structure of regional industries.

3.1.3.3. Education and the degree of scientific and technological development

The development degree of education (EDUCAT) and technology (TECHN) is measured by the average number of students per 100,000 population in colleges and universities and the turnover of the technology market.

3.1.3.4. Foreign trade and consumption demand structure

Foreign trade structure (FTS) is measured by the foreign direct investment (FDI) ratio to GDP. Consumption structure (CS) is measured by the ratio of retail and social goods turnover.

3.1.3.5. Capital deepening and economic fluctuation

In order to know the capital deepening degree (CDD) of each province, this paper calculates the ratio of the fixed capital stock of each province to the total employment of the province. Moreover, the actual growth rate is used to measure the regional economic fluctuation (EV).

TABLE 4. DESCRIPTIVE STATISTICS OF VARIABLES

variable	n	average	standard deviation	minimum	maximum
TCL'	271	-0.014	0.123	-0.898	0.515
TIOV	271	9312.516	7978.824	472.380	39398.460
ILF	271	312.576	329.994	9.804	1489.479
GDP	271	23866.616	19556.738	1370.400	107986.900
TRLF	271	2728.848	1803.054	301.000	7142.000
PDI	271	0.001	0.124	-0.833	0.577
DEE	271	-0.108	0.576	-3.128	2.255
ln RGDP	271	0.341	0.150	0.077	0.895
ln RISL	271	10.812	0.433	9.706	12.009
ln EDUC	271	1.174	0.665	0.518	5.169
ln TECH	271	7.818	0.283	6.987	8.633
FTS	271	13.828	1.758	8.642	17.858
CS	271	0.005	0.004	0.000	0.020
ln CDD	271	0.048	0.031	0.001	0.179
EV	271	20.603	10.842	1.741	73.846

3.2. Propose assumptions and build models

3.2.1. make assumptions

According to the actual situation of literature research and path dependence, the following assumptions are put forward:

3.2.1.1. The first hypothesis

H1: The better the development of the digital economy, the more obvious it will be to break the path dependence effect.

3.2.1.2. The second hypothesis

H2: The better the regional development level and the more developed the industrial structure of a province and city, the easier it is for the region's development to break through the original development path restrictions.

3.2.1.3. The third hypothesis

H3: The higher the province's or city's education level, the less likely it is to be locked in the original development path.

3.2.1.4. The fourth hypothesis

H4: The higher the degree of scientific and technological development, the more developed the foreign trade and the more reasonable the consumption demand structure, the harder it is for the development path of provinces and cities to solidify.

3.2.1.5. The fifth hypothesis

H5: The higher the degree of capital deepening and the greater the degree of economic fluctuation, the more benign the development path of provinces and cities will be.

3.2.2. Model setting

Based on the above assumptions, a comprehensive panel model with the path dependence effect index as the explanatory variable and the digital economic evaluation index as the core explanatory variable is established:

$$PDI_{it} = \gamma_0 + \gamma_1 DEE_{it} + \gamma_2 \ln RGDPPC_{it} + \gamma_3 \ln RISL_{it} + \gamma_4 \ln EDUCAT_{it} + \gamma_5 \ln TECHN_{it} + \gamma_6 FTS_{it} + \gamma_7 CS_{it} + \gamma_8 \ln CDD_{it} + \gamma_9 EV_{it} + \delta_{it} + \mu_{it} \quad (12)$$

Where PDI_{it} represents the degree of path dependence,

γ_0 is a constant term, δ_{it} represents the regional effect, and μ_{it} is a random disturbance term. After the multicollinearity test, heteroscedasticity test and autocorrelation test, the regression of the fixed effect model and random effect model was carried out. Firstly, the multicollinearity test shows that the VIF of each explanatory variable is not more than 10, and there is no strong correlation. In White's test, P=0.0869, it is considered that there is no heteroscedasticity at a 90% significance level. The Breusch-Godfrey LM test shows that Prob > chi2=0.0843, and it can be considered that there is no autocorrelation of the indicators at a 90% significance level. Houseman test showed that Prob>chi2 =0.0000, the fixed effect model was selected. See Table 4 for the description of each index of the fixed-effect model (FE).

3.3. Regression result

According to the regression results of panel data in Table 4, we can see that the digital economic evaluation index, capital deepening degree, and economic fluctuation degree on the path dependence effect is significant at 5% and 1%, respectively, meeting assumptions 1 and 5. However, the level of technological development, the structure of foreign trade and the structure of consumer demand have a weak influence on the path dependence effect, so hypothesis 4 cannot be verified, which shows that it has no significant effect on breaking through the path dependence effect. The influence of regional development level, regional industrial structure level and educational development level on path dependence is significant at 1% and 5%, respectively. It is worth noting that the coefficients of these indicators are positive. Therefore, hypothesis 2 and hypothesis 3 are rejected, and it is considered that the higher these indicators are, the more pronounced the inhibition effect on the breakthrough of path dependence is.

TABLE 5. REGRESSION RESULTS OF FIXED EFFECT MODEL

Var	Coef.	Std. Err.	t	P>|t|	VIF
DEE	-1.079**	0.580	1.860	0.064	4.03
ln RGDPPC	2.047***	0.299	6.850	0.000	4.29
ln RISL	0.249**	0.165	1.510	0.052	2.01
ln EDUCAT	0.642**	0.430	1.490	0.057	1.90
ln TECHN	-0.006	0.051	-0.110	0.912	2.43
FTS	-6.089	13.666	-0.450	0.656	1.57
CS	2.967	2.128	1.390	0.165	1.32
ln CDD	-3.190***	0.152	-20.950	0.000	3.79
EV	-10.329***	1.752	-5.900	0.000	2.76
_CONS	-17.689***	3.922	-4.510	0.000	-
R^2(within)	0.657	-	-	-	-
obs	270.000	-	-	-	-
F test	12.370	-	-	-	-

Note:*,**,*** means that it passed the significance test of variable T value at the significance levels of 10%, 5% and 1% respectively.

3.4. Robustness test

In order to test the robustness of the model results, this paper replaces the core explanatory variable with its second lag term DEE(-2) and then tests the fixed effect. The new fixed effect model results are shown in Table 5, and the core explanatory variables are still significant, so the model can be considered robust.

TABLE 6. REGRESSION RESULTS OF TWO-STAGE LAG FIXED EFFECT MODEL

Var	Coef.	Std. Err.	t	P>|t|
DEE(−2)	-0.207***	0.088	-2.350	0.020
ln RGDPPC	0.183**	0.106	1.730	0.086
ln RISL	0.068	0.057	1.180	0.238
ln EDUCAT	-0.007	0.184	-0.040	0.970
ln TECHN	-0.027	0.021	-1.280	0.202
FTS	-1.250	5.503	-0.230	0.821
CS	0.547	1.143	0.480	0.633
ln CDD	-0.132***	0.055	-2.410	0.017
EV	-0.027	0.871	-0.030	0.975
_CONS	-1.269	1.360	-0.930	0.352
R^2(within)	0.076	-	-	-
obs	210.000	-	-	-
F test	0.850	-	-	-

Note:*,**,***as same meaning as above.

4. CONCLUSION AND ENLIGHTENMENT

This paper studies the influence of the digital economy on the path dependence effect, construct several related control variables, and draws the following conclusions: First, the development degree of the digital economy, the deepening degree of capital and the deepening degree of economic fluctuation are conducive to breaking through the path dependence of regional and municipal development. Secondly, the higher the level of regional development, regional industrial structure and educational development, the greater the welfare effect. The more reluctant they are to change the original development model, the more unfavourable it is to reduce the level of path dependence. Thirdly, the level of technological development, the structure of foreign trade and the structure of consumer demand have little effect on improving the path dependence.

Based on this, this paper gets the following inspirations: First, all provinces and cities should speed up the development of the digital economy, introduce new vitality to local development, drive the transformation of local entity enterprises through the vigorous development of the digital economy, actively build new formats, and breakthrough the solidification mode of the original industry. Secondly, provinces and cities can increase investment in fixed assets, maintain sound economic growth, and create a good capital environment for local economic development. At the same time, increasing the degree of capital deepening can effectively improve the development path locking of industries endowed with non-capital factors. Finally, all provinces and cities should rationally adjust the proportion of secondary industries and introduce tertiary industries with high added value, such as hi-tech industries. Areas with high economic development levels and high educational development levels should also pay attention to risk prevention to avoid being caught in the dilemma of solidification of economic development mode by relying too much on the dividends brought by the current development model.

This paper studies the influence of the digital economy on the path dependence effect, and the follow-up research can also study the influence of path dependence on the development of the digital economy in turn. In addition, this paper studies the influence of comprehensive indicators of the digital economy on path dependence, and we can continue to study the influence of inclusive finance and digital transactions on path dependence. Finally, the follow-up research can also study the spatial heterogeneity of the digital economy and path dependence.

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