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Analysis of Spillover Effects of Digital Economy—An Empirical Study Based on Time Series Input-Output

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Abstract: *The purpose of this study is to analyze the composition and relationship of the factors that affect the output of digital economy. Theoretically, this study redefined the digital economy, whose essence is the component and economic forms of economic reproduction of digital elements. Empirically, we take Zhejiang Province, who has developed as the digital economy highland of China, as the research object. To assess the output effects of the digital economy, this study constructed an evaluation system comprising five indicators and 22 sub-indicators. Based on statistical data from 1998 to 2018, principal component analysis, unit root test and co-integration analysis were conducted in this paper, and then a vector autoregressive model was constructed. The results showed that, when other conditions remain unchanged, each unit of human capital and technology development will increase by 0.814 units and 1.112 units of digital economic output in Zhejiang Province, respectively. However, the variables of ICT application and infrastructure are in a state of stagnation due to the complete construction. The continuous investment cannot bring about significant growth but may occupy too many resources such as limited capital policies or drag down the digital output. Therefore, while increasing the investment in human capital variables and technology development variables, we need to reduce the investment in ICT application variables and infrastructure variables to maximize the digital economy's output efficiency.*

Keywords: *digital economy; unit root test; time series analysis; cointegration test; principal component analysis; VAR; Zhejiang*

1. Introduction

The digital economy is a new engine and a new factor of production for high-quality economic development and transformation. With the transition of the traditional economy to a digital economy fuelled by digital technology, it has become a hot topic in academia to explore the linkage effects of the digital economy in production and life and to extend its boundaries. As a derivative form of ICT industry change, the digital economy is a new economic form spiced up by information and communication technology. The digital economy was first named the "Internet Age of Intelligence". Tapscott (1996) first proposed that the digital economy could combine elements such as artificial intelligence and creativity [1] to achieve breakthroughs in ICT and network intelligence. Under the blessing of new technologies, industrial wealth is created and social development is promoted.

With the rapid breakthroughs in ICT and its wide application in industry, definitions and insider knowledge about the digital economy are changing and being enriched and refined with the development of areas such as digital scenarios, digital needs and digital products. Innovation remains the main driver for the development of the ICT industry (Liu and Miao, 2022)[2]. In most cases, different countries have adopted regulatory frameworks to facilitate the development of the digital economy. The widespread use and innovation of digital technologies has empowered individuals, businesses, organisations and governments with a range of digital applications. Empowered by such digital capabilities, they can take purposeful and promising actions in the digital environment. And, this capability, which we can also understand as the scale of diffusion of the digital economy.

The digital economy is driven by integrating information, computing, and communication. It is an economic system that makes use of ICT and, in addition, a form of economy that uses digital technology as a factor of production. The integration of ICT in the economic system has brought about the widespread growth of e-commerce. The digital economy promotes a reliance on electronic means for networks of intermediate information flows of goods and services. Its essence is digital technological innovation and rapid networking (Barefoot et al., 2018)[3]. The combination of digitisation and the Internet represents the trend and form of development of generic technologies.

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With the help of the digital technologies, it has triggered changes, disruptions and creations in economic and social activities. A large combination of digital elements and technology can be called "new economy". This new technology can bring new activities and products, but also establishing new levels and forms of connection between different ideas and participants, resulting in a wide range of new combinations.

As a particular form of economy, ideally, the boundaries and concepts regarding the digital economy should change over time, i.e. any economic activity that is largely enhanced by or through digital investment can be called a digital economy. At the same time, relying on new production factors such as ICT and data elements can facilitate the amplification, superposition and multiplier effects of digital production factors on the economy (Moroz, 2017)[4]. The digital economy can both disrupt existing economic rules and potentially reshape existing consumer behaviour and business models; in addition, it can also create new economic forms, economic rules, economic processes, economic systems and other new economic products. We can nurture new industries and new dynamics, accelerate the digitisation and digital industrialisation of industries, improve the productivity of the entire factor and thus extend the industrial chain of the digital economy. In addition, the digital economy can help foster new economic dynamics and build an aggregation based on digital industry, digital society, digital links, digital demand and digital services.

The digital economy, as an economic form that uses data and digital technology as factors of production, is partly or fully aggregated by certain economies (e.g. ICT, data, digital networks or digital models). It is an economic innovation driven by digital elements, which is anchored in digital elements (Sun et al., 2019)[5]. Its essence is the industrial component and economic form of the economic reproduction activities of digital elements. The main innovations of this paper: first, at the theoretical level, this study enriches the research on the digital economy, reveals the connotation and essence of the digital economy. Secondly, at the empirical level, it takes Zhejiang Province, the highland of China's digital economy development, as the research object, an evaluation system including five primary indicators and 22 secondary indicators was constructed, using principal component analysis, unit root test, and cointegration test, and constructed a vector autoregressive model, and conducted a confirmatory analysis based on statistical data from 1998 to 2018, which is representative and predictable. Using Zhejiang Province of China as an empirical case to examine the development characteristics of the digital economy in Zhejiang Province from 1998 to 2018.

2. Research Methods and Data

2.1 The index system

The innovation factor remains the main driver of ICT industry development (OECD, 2017)[6]. In most cases, economic growth can be effectively driven by adapting to economic growth, technological innovation and regulatory frameworks. Technological innovation brings strong digital capabilities to individuals, organisations and businesses, which in turn strengthen their ability to take purposeful and potential action on digital systems[7]. Because the digital economy is a concept that has not yet been fully defined, there are various concepts. There is no rigid boundary of the digital economy, and the evaluation indicators are limited (Milošević et al., 2018)[8], and there are some differences. In order to explore the output effects and influencing factors of the digital economy, considering that there are few regions in China with a relatively well-developed digital economy. In this study, Zhejiang Province, the highland of China's digital economy, was selected as a sample, and provincial data from 1998-2018 were chosen to construct a digital economy evaluation system by selecting relevant indicators from five aspects (Table 1).

The five first-level indicators are ICT Applications (X1-X5), Human Resource (X6-X9), Infrastructure (X10-X13), Technological Development (X14-X17), and the Output of Digital Economy (X18-X22). The 22 indicators are: Number of Mobile Phones Coverage (X1), Number of Telephone Coverage (X2), Number of households using Mobile Phones (X3), Number of households using Mobile Broadband (BB) (X4), Number of Fixed Broadband (BB) Users (X5), Number of College Students per 10k People (X6), Proportion of ICT employees in Total Employment (X7), Proportion of Scientific Research and Technical Services in Total Employment (X8), Proportion of R&D personnel in Total Employment (X9), Proportion of Broadcast Comprehensive Population Coverage (X10), Proportion of TV Comprehensive Coverage (X11), Relative Length of Long-Distance Optical Cable (X12), Number of Mobile Phone Switchboard (X13), Number of R&D Investment Per Capita (X14), Number of Patents Granted (X15), Number of Technology Market Turnover (X16), Proportion of R&D

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Investment in GDP (X17), Main Business Income of Electronic Information Industry (X18), Main Business Income of Electronic Information Manufacturing Industry (X19), Total Telecommunications Business in the Communications Industry (X20), Postal Business Volume (X21), Index of the digital economy (X18+X19+X20+X21)/GDP (X22), as in shown in Table 1.

Table 1: Digital Economy Evaluation System

Index category	Index	Unit
ICT Applications	X1 Number of Mobile Phones Coverage	(%)
	X2 Number of Telephone Coverage	(%)
	X3 Number of households using Mobile Phones	(10k households)
	X4 Number of households using Mobile Broadband (BB)	(10k households)
	X5 Number of Fixed Broadband (BB) Users	(10k households)
Human Resource	X6 Number of College Students per 10k People	(persons)
	X7 Proportion of ICT employees in Total Employment	(%)
	X8 Proportion of Scientific Research and Technical Services in Total Employment	(%)
	X9 Proportion of R&D personnel in Total Employment	(%)
Infrastructure	X10 Proportion of Broadcast Comprehensive Population Coverage	(%)
	X11 Proportion of TV Comprehensive Coverage	(%)
	X12 Relative Length of Long-Distance Optical Cable	(km /10k persons)
	X13 Number of Mobile Phone Switchboard	(10k households)
Technological Development	X14 Number of R&D Investment Per Capita	(Yuan)
	X15 Number of Patents Granted	(Item)
	X16 Number of Technology Market Turnover	(10k Yuan)
	X17 Proportion of R&D Investment in GDP	(%)
Output of Digital Economy	X18 Main Business Income of Electronic Information Industry	(100 million Yuan)
	X19 Main Business Income of Electronic Information Manufacturing Industry	(100 million Yuan)
	X20 Total Telecommunications Business in the Communications Industry	(100 million Yuan)
	X21 Postal Business Volume	(100 million Yuan)
	X22 Index of the digital economy (X18+X19+X20+X21)/GDP	(%)

During 1998-2018,as for the ratio of the maximum value to the minimum, the ratios of indicator X21(121.920) and X14 (104.345) are greater than 100,the rations of X4 (68.370), X15 (63.667), X18 (60.262) and X3 (50.975) are between 50-100 ,the ratios of indicator X19 (42.060), X1 (40.162), X16 (38.940), X5 (36.610), X20 (29.583), X13 (27.447), X9 (13.503), X7 (12.750), X17 (12.381) and GDP (11.268) are between 10-50 ,and the rations for RGDP (8.771), X2 (8.254), X8 (8.123), X6 (7.542), X22 (4.426), X12 (4.178), Population (1.287), X10 (1.160) and X11 (1.084) are between 1-10. It can be seen that, when the total population of Zhejiang Province only increased by 28.7% from 1998 to 2018, Zhejiang's GDP increased by 11.268 times, and RGDP increased by 8.771 times. At the same time, three indicators increased by more than 100 times. The growth rate of 2 indicators is greater than 100 times, the growth rate of 4 indicators is between 50-100 times, and the growth rate of 10 indicators is between 10-50 times. There are nine indicators whose growth rate is between 1-10 times. That is, the overall sample has a large growth in 21 years.

2.2. Data sources

Zhejiang, located on the southeast coast of China, has a total area of 105,500 sq km. in October 2019, Zhejiang Province was selected as China's national digital economy innovation and development pilot zone. in 2021, the digital economy development index of Zhejiang Province was 112.8%, and the proportion of R&D expenditure in the digital economy core industry equivalent to business revenue was 2.01%. The new product output rate of the manufacturing industry in the core digital economy industry reached 57.6%, 17% higher than that of industries above the scale, and the added value of the core digital economy industry was RMB 834.83 billion in 2021. Zhejiang Province has taken the digital economy as the "No. 1 project". It taken the lead in promoting local legislation on the digital economy,

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and cultivated an atmosphere of promoted word economic output (Lin and Jiang, 2019)[9]. In 2020, with "Digital Zhejiang" as the goal, Zhejiang implement the "10 million" plan for digital industry: build 100 innovation platforms, build provincial digital economy innovation and development pilot zone; implement 100 billion digital economy projects, attract 100 high-end talents and 1000 innovation projects; cultivate trillion emerging industries, and strive to make the business income of core industries of digital economy exceed 2 trillion yuan.

2.3. Methods

2.3.1. Principal component analysis

Principal component analysis (PCA) is an analysis method for multiple variables and is a multidimensional orthogonal linear transformation based on statistical features. It reduces the dimensionality of data by extracting the eigenvalues of multidimensional data, and thus the dimensionality of the data(Pearson, 1901) [10]. Later, scholars such as Hotelling (1933) [11] and Jackson (1959) [12] developed it. There are many books on this topic, even a whole book on PCA variants of special types of data (Flury, 1988) [13]. Later, Jolliffe and Cadima (2016) pointed out that the basic idea of principal component analysis (PCA) [14] leads to a simple, adaptive and insightful low dimensional representation of large data sets.

The PCA method, aims to minimise the loss of information. It does this by creating new uncorrelated variables that have sequentially the greatest variance. New variables, i.e. principal components, are found in the dataset, which in turn solve an eigenvalue/eigenvector problem. The new variables originate from the dataset and are not obtained a priori.Lever et al. (2017) highlight that PCA simplifies the complexity of high-dimensional data and preserves the trends and patterns in the dataset [15].

2.3.2. Unit root test

In view of the original data of the digital economy evaluation index system is time-series data, and there is a large growth trend, it is necessary to test its stability. As Yule (1926) pointed out[16], if the result variable is non-stationary, even if the statistical sample is large, it may be due to the existence of spurious regression. When performing a unit root test, the presence of a pseudo-regression implies that there may not be a true and meaningful relationship between the variables. In this study, we use the enhanced Dickey Fuller test proposed by Dickey and Fuller (1979) to investigate the stationarity of variables by testing for unit roots [17]. Based on the estimation of the three models, ADF tests were performed on both the horizontal observations and the first difference observations.

The model does not have a trend and intercept:

$$\triangle y_t = \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \triangle y_{t-1} + \varepsilon_t \quad (1)$$

The model with intercept only:

$$\triangle y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \triangle y_{t-1} + \varepsilon_t \quad (2)$$

The model with trend and intercept:

$$\triangle y_t = \alpha_0 + \alpha_2 \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \triangle y_{t-1} + \varepsilon_t \quad (3)$$

where:

$\triangle y_t = y_t - y_{t-1}$ is the first difference of the series y_t;

$\triangle y_{t-1} = y_{t-1} - y_{t-2}$ is the first difference of y_{t-1}, etc.;

α, γ and β_i –are parameters to be estimated;

ε_t –is a stochastic disturbance term.

2.3.3 Testing for cointegration of variables

Before Johansen cointegration test, we must use some lag selection criteria to find the lag length corresponding to VAR, thus helping to establish an economic model. Many lag selection criteria have

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been used in a large number of literatures, such as Akaike Information Criterion (AIK), Hannan Quinn Information Criterion (HQIC), series modified LR test statistics, Schwarz Information Criterion (SIC), and Final Prediction Error (FPE).

Akaike information criterion AIC (Akaike, 1974) is a test method used to measure the fitness of an estimated statistical model, and also a basis for model selection [18]. Therefore, AIC is defined as:

$$AIC = e^{\frac{2k}{n}} \frac{\sum \hat{u}_i^2}{n} = e^{\frac{2k}{n}} \frac{RSS}{n} \tag{4}$$

In the formula, k represents the number of regression factors (including intercept), and n represents the number of observations. For mathematical convenience, equation (10) can also be written as:

$$\ln(AIC) = \left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right) \tag{5}$$

where ln (AIC) = natural log of AIC and 2k/n = penalty factor.

Schwarz Information Criterion SIC (Schwarz, 1978) is a measure of the goodness of fit of an estimated statistical model and can also be used for model selection. It is defined as

$$SIC = n^{\frac{k}{n}} \frac{\sum \hat{u}_i^2}{n} = n^{\frac{k}{n}} \frac{RSS}{n} \tag{6}$$

Transforming Equation (12) in natural logarithm form, it becomes (Equation (13));

$$\ln(SIC) = \frac{k}{n}\ln(n) + \ln\left(\frac{RSS}{n}\right) \tag{7}$$

where $\frac{k}{n}\ln(n)$ is the penalty factor.

Hannan-Quinn information criterion HQIC (Hannan & Quinn, 1979) is a measure of the fit of an estimated statistical model [19]. It is often used as a criterion for selecting evaluation models. It is defined as:

$$HQIC = 2k\ln(\ln n) + n\ln\left(\frac{RSS}{n}\right) \tag{8}$$

In the formula, n represents the number of observations, and k represents the number of model parameters. RSS represents the sum of squares of the residuals generated by the statistical model.

The model with the lowest AIC, SIC and HQIC scores is usually preferred for consideration of different models in the research.

3. Results

3.1. Principal component analysis

After principal component analysis, it was found that the factor ICT Applications (ICTA) generated after index X1-X5 is rotated, the cumulative contribution rate of the principal component is 93.364%; the factor Human Capital (HUMC) generated after the index X6-X9 is rotated, the cumulative contribution rate of the principal component is 89.722%; the factor Infrastructure (INFR) generated after the indicators X10-X13 are rotated, the cumulative contribution rate of the principal components is 88.187%; the factor Technological Development (TECD) generated after index X14-X17 is rotated, the cumulative contribution rate of principal components is 87.901%; the factor Output of Digital Economy (ODE) generated after index X18-X22 is rotated, the cumulative contribution rate of the principal component is 82.779%. The cumulative contribution rate of the principal components of the 22 indicators is 92.781%, and the cumulative contribution rate is greater than 80%, with less

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information loss. Therefore, this study believes that the newly generated comprehensive variables (factors or principal components) integrate most of the information of the original indicators and can better represent the original indicators. Furthermore, this study replaced the original data with new variables for subsequent analysis.

3.2. Unit root test

In order to test the relationship among the indicators of digital economy in Zhejiang Province, such as ICTA, HUMC, INFR, TECD and ODE, the annual data from 1998 to 2018 were used in this study. According to data analysis, this paper uses the enhanced Dickey Fuller (ADF) test to test the stationarity of the time series of ICTA, HUMC, INFR, TECD and ODE variables, and conducts unit root test for the five new variables (Table 2).

Table 2: Unit Root Test of Variables

Variables	Test Type (C, T, K)	ADF Value	1% level	5% level	10% level	Result
ICTA	(C, 0, 0)	1.499	-3.887	-3.052	-2.667	Unstable
HUMC	(C, 0, 0)	0.794	-3.809	-3.021	-2.650	Unstable
INFR	(C, 0, 0)	-0.441	-2.692	-1.960	-1.607	Unstable
TECD	(C, 0, 0)	3.253	-3.920	-3.066	-2.673	Unstable
ODE	(C, 0, 0)	2.286	-3.809	-3.021	-2.650	Unstable
△ICTA	(C, 0, 1)	-3.361	-3.887	-3.052	-2.667	stable
△HUMC	(C, T, 1)	-4.356	-4.533	-3.674	-3.277	stable
△INFR	(C, 0, 1)	-4.913	-3.832	-3.030	-2.655	stable
△TECD	(C, 0, 2)	-2.551	-2.700	-1.961	-1.607	stable
△ODE	(C, 0, 2)	-6.116	-3.857	-3.040	-2.661	stable

Note: △ represents the x difference form of the variable; C and T in the test type represent the constant term and the trend term respectively, and K is the lag order, and the selection basis is Akaike info criterion (AIC) Code and Schwarz criterion (SC).

The results of the ADF test show that there is no unit root in the variable ICT Applications (ICTA), that is, the level sequence of the variable is stationary. Among all the variables, Human Capital (HUMC), Infrastructure (INFR), Technological Development (TECD), and Output of Digital Economy (ODE) all have unit roots, that is, the horizontal series of the four variables are all non-stationary. The analysis shows that the first-order difference of the variables Human Resource and Infrastructure is stationary, and both are first-order single integer sequences. The second-order difference of Technological Development and Output of Digital Economy is stationary, and both are second-order single integer sequences. They can be further tested for the cointegration relationship.

3.3. Cointegration test

Furthermore, we use the cointegration test of variables to verify any long-term equilibrium relationship between ICTA, HUMC, INFR, TECD and ODE. Table 3 summarizes the results of Johansen's co integration grade test.

Table 3: Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.973	126.897	69.819	0.000
At most 1 *	0.734	58.068	47.856	0.004
At most 2 *	0.628	32.917	29.797	0.021
At most 3 *	0.386	14.139	15.495	0.079
At most 4 *	0.226	4.863	3.841	0.027

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The cointegration analysis results show that "None *" means that there is zero cointegration relationship "in the original hypothesis. The trace statistic under this hypothesis is 126.897, and the critical value of 5% is 69.819. Therefore, the original hypothesis is rejected, indicating that there is at least one cointegration relationship. In the "At most 3 *" hypothesis, the original hypothesis indicates that there are at most three cointegration relationships. The trace statistic under this assumption is 14.139, while the critical value of 5% is 15.495, which is less than the critical value. Therefore, we

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accept the original hypothesis and show that there are at most three Cointegration relationships. The existence of cointegration means that there is a long-term stable equilibrium relationship between variables.

It can be seen from the results in Table 4 that when testing the Max-Eigen statistics, "None *" means that there is a "zero cointegration relationship" in the original hypothesis. Under this hypothesis, the Max-Eigen statistic is 68.828, and the critical value of 5% is 33.877. Therefore, the original hypothesis is rejected, indicating that there is at least one cointegration relationship. In the "At most 1*" hypothesis, the original hypothesis means "at most one cointegration relationship." Under this assumption, the Max-Eigen statistic is 25.152, while the critical value of 5% is 27.584, and the Max-Eigen statistic is less than the critical value. Therefore, we accept the original hypothesis, and it shows that there is at most one cointegration relationship. The existence of cointegration means that there is a long-term stable equilibrium relationship between variables,as is shown in Table 4.

Table 4: Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.973	68.828	33.877	0.000
At most 1 *	0.734	25.152	27.584	0.099
At most 2 *	0.628	18.778	21.132	0.104
At most 3 *	0.386	9.276	14.265	0.264
At most 4 *	0.226	4.863	3.841	0.027

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

3.4. Long-term equilibrium relationship estimation

Because there are 21 statistical samples in this study, five endogenous synthetic variables need to be estimated, and the Johansen test may have a fat tail effect under the previous samples, which has a substantial mean deviation. Therefore, the Johansen test was used in this study to test the existence or otherwise of cointegration relationships between input-output variables in the digital economy. In addition, the vector autoregressive (VAR) econometric model proposed by Sims (1980)[20] was used to verify the long-run equilibrium relationship between variables.

In the traditional econometric modelling system, the relationships between variables are generally established based on some economic theories. However, the established economic theories hardly reflect the dynamic relationships between variables in a comprehensive manner. Due to the presence of endogenous variables, which may appear at the left or right end of the assessed model. As a commonly used model, VAR models can be used to analyse and predict the time series relationships of multiple interrelated variables. Also, the vector autoregressive model, which ideally eliminates exogenous variables, has the following expression.

$$Y_t = A_1 Y_{t-1} + L + A_p Y_{t-p} + \mu_t$$

Where Y_1 is the k-dimensional endogenous variable vector, P is the lag order, k* k-dimensional matrix A_1, L, A_p are the coefficient matrix to be estimated, and μ_t is the random error term. Due to the limited sample size, this study compared the statistics of Schwarz Criterion and Akaike Information Criterion and selected the saving model with lag order p of 2 to evaluate the variables. The regression results are shown in Table 5.

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Table 5: Vector Autoregressive Estimation Results based on 2nd Order Lag

	ODE	HUMC	INFR	ICTA	TECD
ODE(-1)	1.667	0.620	1.943	-0.018	0.200
	(-0.559)	(-0.615)	(-0.885)	(-0.322)	(-0.300)
	[2.980]	[1.007]	[2.195]	[-0.057]	[0.667]
ODE(-2)	0.166	0.257	1.035	0.731	-0.031
	(-0.589)	(-0.648)	(-0.932)	(-0.339)	(-0.316)
	[0.281]	[0.396]	[1.111]	[2.156]	[-0.098]
HUMC(-1)	-0.532	0.011	0.034	0.144	-0.245
	(-0.405)	(-0.445)	(-0.640)	(-0.233)	(-0.217)
	[-1.315]	[0.026]	[0.054]	[0.617]	[-1.127]
HUMC(-2)	-0.146	-0.267	-0.017	-0.127	-0.058
	(-0.335)	(-0.369)	(-0.530)	(-0.193)	(-0.180)
	[-0.436]	[-0.725]	[-0.033]	[-0.659]	[-0.323]
INFR(-1)	0.407	0.547	0.129	-0.339	0.160
	(-0.357)	(-0.393)	(-0.565)	(-0.206)	(-0.191)
	[1.141]	[1.391]	[0.228]	[-1.647]	[0.838]
INFR(-2)	0.556	0.234	0.310	-0.128	0.415
	(-0.372)	(-0.410)	(-0.589)	(-0.214)	(-0.200)
	[1.493]	[0.572]	[0.526]	[-0.596]	[2.081]
ICTA(-1)	0.819	0.212	1.296	0.867	-0.062
	(-0.382)	(-0.421)	(-0.605)	(-0.220)	(-0.205)
	[2.142]	[0.503]	[2.143]	[3.938]	[-0.303]
ICTA(-2)	-0.539	0.143	-0.542	0.129	0.087
	(-0.242)	(-0.266)	(-0.382)	(-0.139)	(-0.129)
	[-2.233]	[0.537]	[-1.420]	[0.930]	[0.670]
TECD(-1)	-0.526	-0.835	-1.421	0.716	0.772
	(-0.561)	(-0.617)	(-0.888)	(-0.323)	(-0.301)
	[-0.937]	[-1.352]	[-1.601]	[2.216]	[2.564]
TECD(-2)	-0.400	0.319	-1.152	-1.104	-0.136
	(-0.622)	(-0.684)	(-0.984)	(-0.358)	(-0.334)
	[-0.643]	[0.466]	[-1.171]	[-3.083]	[-0.407]
C	0.167	0.314	0.158	0.076	0.239
	(-0.131)	(-0.144)	(-0.207)	(-0.075)	(-0.070)
	[1.280]	[2.183]	[0.763]	[1.003]	[3.411]
R-squared	0.994	0.992	0.985	0.996	0.998
Adj. R-squared	0.987	0.982	0.965	0.991	0.996
Sum sq. resids	0.100	0.121	0.250	0.033	0.029
S.E. equation	0.112	0.123	0.177	0.064	0.060
F-statistic	135.232	101.108	51.177	203.443	436.783
Log likelihood	22.879	21.065	14.166	33.364	34.721
Akaike AIC	-1.250	-1.059	-0.333	-2.354	-2.497
Schwarz SC	-0.704	-0.513	0.214	-1.807	-1.950
Mean dependent	0.122	0.151	0.137	0.236	0.146
S.D. dependent	0.972	0.926	0.951	0.686	0.935
Determinant resid covariance (dof adj.)		4.56E-12			
Determinant resid covariance		6.04E-14			
Log likelihood		154.362			
Akaike information criterion		-10.459			
Schwarz criterion		-7.725			
Number of coefficients		55.000			

Note: 1. Standard errors in ( ) & t-statistics in [ ]. 2. ODE= Output of Digital Economy, HUMC= Human Capital, INFRA= Infrastructure, ICTA= ICT Applications, TECD= Technological Development.

It can be seen from the Vector Autoregression results (Table 5) that the top-level data are the adoption number estimation results of the model, the standard deviation of the estimation coefficient,

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and t-test statistics. The middle part is the correlation test results of each sub equation, and the bottom part is the statistics of the whole vector autoregressive model. The results show that the five variables' R-squared values are in the range of 0.985-0.998, explaining the original variables greatly. When considering the adjustment of the variables, the adj. R-squared values are still between 0.965 and 0.996, which can explain the original variables' information at a great level. Moreover, the F value is at a high level, which means that this study cannot reject the hypothesis that all lagging terms are statistically significant. The relationship matrix of parameter estimation results of variables is as follows.

$$Y_t = \begin{bmatrix} 1.667 & -0.532 & 0.407 & 0.819 & -0.526 \\ 0.620 & 0.011 & 0.547 & 0.212 & -0.835 \\ 1.943 & 0.034 & 0.129 & 1.296 & -1.421 \\ -0.018 & 0.144 & -0.339 & 0.867 & 0.716 \\ 0.200 & -0.245 & 0.160 & -0.062 & 0.772 \end{bmatrix} * Y_{t-1} + \begin{bmatrix} 0.166 & -0.146 & 0.556 & -0.539 & -0.400 \\ 0.257 & -0.267 & 0.234 & 0.143 & 0.319 \\ 1.035 & -0.017 & 0.310 & -0.542 & -1.152 \\ 0.731 & -0.127 & -0.128 & 0.129 & -1.104 \\ -0.031 & -0.058 & 0.415 & 0.087 & -0.136 \end{bmatrix} * Y_{t-2} + \begin{bmatrix} 0.167 \\ 0.314 \\ 0.158 \\ 0.076 \\ 0.239 \end{bmatrix}$$

$ODE = 1.667\ ODE_{t-1} + 0.166\ ODE_{t-2} - 0.532\ HUMC_{t-1} - 0.146\ HUMC_{t-2} + 0.407\ INFR_{t-1} + 0.556\ INFR_{t-2} + 0.819\ ICTA_{t-1} - 0.539\ ICTA_{t-2} - 0.526\ TECD_{t-1} - 0.400\ TECD_{t-2} + 0.167$

In order to obtain a simpler long-term equilibrium relationship between variables, we assume:

ODE=ODEt-1=ODEt-2, HUMC=HUMC t-1=HUMC t-2, INFR=INFR t-1=INFR t-2, ICTA=ICTA t-1=ICTA t-2, TECD=TECD t-1=TECD t-2

After simplification, the long-term equilibrium relationship equation between the dependent variable and the independent variable is:

ODE= 0.814 HUMC – 1.156 INFR - 0.336 ICTA+ 1.112 TECD - 0.200

The results show a long-term stable relationship between digital economic output and human capital, infrastructure, ICT Applications, and technology development in Zhejiang Province from 1998 to 2018. With other conditions unchanged, every 1% increase in human capital activities can drive the digital economic output of Zhejiang Province to increase by 0.814%. Similarly, every one percentage point increase in technology development activities around the digital economy can drive the output of digital economy growth by 1.112 percentage points. ICT application activities and infrastructure activities may occupy too many resources such as limited funds and policies.

4. Conclusions and Discussion

4.1. Conclusions

This research believes that the digital economy is an economic innovation driven by digital elements, which include data, ict, digital technology, digital models, etc. As well as the economic form innovation brought by scene innovation, demand innovation, model innovation, etc. derived from data elements. Its essence is the industrial component and economic form of economic reproduction activities of digital elements. This study uses the 1998-2018 time-series data of Zhejiang Province, China. Firstly principal component analysis, unit root test. Secondly, a Vector Autoregressive model (Sims, 1980) was used to conduct an empirical analysis of the influence of digital economy components on the Output of digital economy growth[20].

The results show that there is a long-term equilibrium relationship among variables such as ICTA, HUMC, INFR, TECD, and ODE. At the same time, during 1998-2018, the digital economic output of Zhejiang Province has a long-term and stable relationship with human capital, infrastructure, ICT applications, and technology development. With other conditions unchanged, every 1% increase in human capital activities can drive the digital economic output of Zhejiang Province to increase by 0.814%. Similarly, every one percentage point increase in technology development activities around the digital economy can drive the Output of digital economy growth by 1.112 percentage points. ICT applications activities and infrastructure activities may occupy too many resources such as limited funds and policies.

4.2. Discussion

Due to the fuzziness of the digital economy boundary (Bukht and Heeks, 2017)[21], relevant indicators are chosen as many as possible to constructs an evaluation system. The control variables of this study mainly include the ICT applications composite variable (X1-X5), human capital composite variable (X6-X9), infrastructure composite variable (X10-X13), technology development composite variable (X14-X17), and digital economic output composite variable (X18-X22). Meanwhile, human capital, infrastructure, and technology development. From the VaR results, it can be seen that from 1998 to 2018, technology development and human capital variables have the most significant contribution towards the output of digital economy is more prominent. Therefore, this study has important representativeness, predictability. Zhejiang, which is representative and predictable for studying and analysing the input-output effect of China's digital economy. It analyses the factors influencing the output of the digital economy and enriches the existing research on the digital economy. Thirdly, in order to reveal the internal development trend in a long period, the time series analysis method is used, and the vector autoregressive model (VaR) is constructed. The influence efficiency of the factors that affect the output of digital economy is revealed by rigorous analysis.

From the above results, we can see some policy implications. Increasing investment in human capital and technological development can enhance the overall competitiveness of the ICT industry and strengthen the foundation of the digital economy support. On the basis of maintaining the existing infrastructure and ICT Applications level, such as promoting the development of the information and communication industry, cultivating scientific research and technical services, and increasing the R&D investment of the whole society. In order to create a digitally productive environment, there is a need to expand the scale of information talent in higher education institutions, increase the supply of highly qualified personnel, and create incentives and protection for innovation.

At the same time, it brings huge economic benefits and brings certain hidden risks. Consumers have a higher risk of privacy leakage during online consumption. Simultaneously, in the process of digitizing a large amount of data composed of citizens' private data, commercial data, and government statistical data, consumers' data privacy protection work shows a certain lag. In addition, regulators should strengthen cooperation with data storage departments, enhance communication and collaboration between consumers and data protection departments, and improve data security supervision sandbox strategy. At the same time, we will accelerate the promotion of relevant legislation on data privacy and data sharing jurisdiction, and do a good job in cross regional cooperation in the field of digital economy (Miao, 2021)[22]. Promote the construction of integrated supervision between enterprises and industries to maximize the digital process's benefits and reduce its potential risks.

4.3. Limitations of the study

The digital economy has been mentioned for the first time by Tapscott (1996) after 24 years of development[1]. Since the digital economy is a concept that has not yet been fully defined and has a variety of concepts, there is no rigid boundary. When constructing the evaluation system, there will be differences due to the research object's characteristics, data availability, and representativeness. When analyzing the provincial level in Zhejiang Province, China, because of the restriction of data availability and representativeness of statistical indicators. With the improvement of statistical indicators, more indicators should be added to verify the various relationships between variables. Moreover, we should have in-depth studies exploring the impact of the digital economy on economic growth, regional education, and human capital and technological progress.

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