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Analysis of the Impact of the Digital Economy on Employment in China

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Abstract: As China's economy gradually transitions towards high-quality development, the growth of the digital economy has created numerous new employment opportunities. To verify the specific impact of the digital economy on labor demand, this paper examines both employment quantity and employment structure. Using relevant data variables from 30 provinces and cities in China from 2012 to 2022, this study applies the entropy method to develop a comprehensive index for the digital economy. This index is then used in regression analyses with total employment and high- and low-technology intensity employment. The findings suggest that overall, the development of the digital economy positively contributes to the growth in labor demand, manifested in the promotion of high-tech employment and the suppression of low-tech employment.

Keywords: digital economy, employment structure, employment quantity.

1. Introduction

The digital economy, a much-discussed topic in recent years, has had a significant impact on various industries. In recent years, China's digital economy has developed rapidly, becoming a key emerging sector and integrating with many industries. Regarding the intersection of the digital economy and employment, on the one hand, the digital economy has created substantial social productivity, potentially leading to new job creation. On the other hand, there is concern about the reduction in labor demand during economic downturns, as well as the potential for artificial intelligence (AI) to replace jobs. Employment has become a major issue of public concern, as it is a crucial livelihood issue that affects social harmony and stability. This makes it an important topic of research. Therefore, this paper investigates how the digital economy influences labor demand.

2. Literature Review

2.1. Research on the Impact of the Digital Economy on Employment Quantity

The impact of the digital economy on employment has been studied from two main perspectives: substitution effects and creation effects. The substitution effect refers to the negative impact on labor market demand as technological advancements, especially the use of robots, replace jobs that were originally performed by humans. Frey and Osborne[1] revealed an important phenomenon in the U.S.: nearly half of all jobs face the potential risk of being automated. Specifically, there is a significant

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negative correlation between the increasing ratio of robots to workers and the proportion of employed individuals. The creation effect, on the other hand, refers to the expansion of production scales due to technological advancements, which lead to the creation of more jobs and, consequently, employment growth. In a study on the impact of internet penetration on employment, Wang Wen et al. pointed out that as internet usage increases annually, new online job demands will arise. Moreover, research shows that the application of the internet and AI helps reduce information asymmetry and increase labor flexibility, providing people with more flexible employment opportunities[2].

2.2. Research on the Impact of the Digital Economy on Employment Structure

With regard to employment structure, the development of the digital economy increases the demand for highly skilled workers while decreasing the demand for low-skilled workers. As a new economic form, the digital economy has the potential to reshape labor force structure. Li Yihan suggests that the substitution effect caused by the development of digital technologies primarily affects workers in medium-skill jobs[3]. By analyzing the employment status of labor in Western countries in the age of automation, it was found that the unemployment rate among blue-collar workers and some white-collar workers engaged in routine tasks has significantly increased. Acemoglu et al. empirically demonstrated that the development of intelligent technologies reduces the demand for medium-skilled workers while increasing the demand for highly skilled workers, indicating that digital technology creates vast opportunities for workers with specialized or advanced skills[4].

2.3. Summary and Commentary

There is ongoing debate regarding whether the impact of the digital economy on employment is positive or negative. Therefore, this paper holds that studying whether the influence of the digital economy on employment is positive or negative has significant research value. Regarding employment structure, although the current classification standards vary, they are all related to the level of technology involved in the job content. Therefore, this paper focuses on the impact of the digital economy on jobs with different levels of technological intensity and uses technology density as the criterion for classification in the structural analysis.

3. Empirical Analysis of the Impact of the Digital Economy on Employment

3.1. Data Selection

3.1.1. Indicator Construction Explanation

Based on relevant existing research, this study selects three main aspects as research criteria. For the digital infrastructure aspect, both mobile infrastructure and fixed facilities were selected. Regarding digital application, the data was divided into enterprise applications and personal applications, with a particular focus on telecommunications services. In terms of digital innovation, the study focuses on both financial investment and workforce composition, selecting corresponding data for analysis.

3.1.2. Digital Economy Indicator Measurement Method

The primary methods used to study the development level of the digital economy are the Entropy Weight Method (EWM) and Principal Component Analysis (PCA). Since the digital economy development index is a composite indicator, multiple sub-indicators must be selected to comprehensively reflect the actual situation. The key to constructing a reasonable indicator lies in assigning different weights to each sub-indicator during the process of synthesizing them into a composite indicator. To ensure rigor and accuracy, this study uses EWM to calculate the digital

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economy development index for cities, which will also provide alternative indicators for robustness tests.

Table 1: Measurement Results of the Digital Economy Development Index in China

Dimension	Meaning	Secondary Indicator	Unit		Data Source
Digital Foundation	Mobile	Mobile Phone Penetration Rate	Per 100 People	0.0216431	China Urban Statistical Yearbook
		Year-End Mobile Phone Users		0.0229314	
	Fixed Facility	Internet Access Broadband Ports	Ten Thousand Ports	0.0242198	
Digital Applications	Personal Applications	Per Capita Telecommunications Service		0.0255081	
		Internet Broadband Access Users	Ten Thousand Households	0.0267965	
	Business Applications	Websites per Hundred Enterprises	Individual	0.0280848	
			Ten Thousand Yuan	0.0293732	
Digital Innovation	Innovation Input	R&D Personnel (Equivalent)	Person-Years	0.0306615	National Bureau of Statistics
		R&D Expenditure	Ten Thousand Yuan	0.0319499	
	Innovation job	Percentage of Computer Services and Software Employees	%	0.1491896	
	Innovation Work	Employment in Information Transmission, Software, and Information Technology Services in Urban Units	Ten Thousand People	0.150478	
	Innovation Work				
	Digital Inclusive Finance	Digital Inclusive Finance Index		0.1517663	Beijing University Financial Research Center

From the table, it can be seen that in the weight calculation of the digital economy, the digital financial inclusion index, the proportion of computer professionals, and the employment ratio in the information transmission, software, and IT service sectors have a relatively significant impact. On

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the other hand, indicators related to mobile infrastructure and digital applications have a smaller weight. This indicates that, when studying the impact of the digital economy on labor demand across varying technological densities, it is more crucial to focus on sectors related to high-tech employment than general infrastructure indicators.

3.2. Research Hypotheses

3.2.1. Hypothesis on the Impact of the Digital Economy on Employment Quantity

The theoretical analysis of the digital economy's impact on employment quantity primarily draws from the perspective of industrial upgrading. Industrial upgrading positively influences employment scale through output growth, structural changes, and climbing the value chain. From the perspective of digital transformation, the new generation of electronic information technology not only provides a solid foundation for the comprehensive digital transformation of society but also drives the emergence of new fields and job opportunities. These new models and industries, based on digital platforms, utilize next-generation digital technologies to deeply transform traditional industries, achieving innovation and surpassing expectations, thus attracting a large labor force.

Therefore, the following hypothesis is proposed: H1: The development of the digital economy has a positive impact on employment quantity.

3.2.2. Hypothesis on the Impact of the Digital Economy on Employment Structure

Existing research indicates that while the digital economy generally has a positive effect on employment, its impact varies across different skill levels. In the digital economy era, low- and medium-skilled labor is more vulnerable to replacement by machines. This substitution effect not only increases the risk of unemployment for these workers but also means that even if they find new jobs, these jobs often lack stability and high wages. In contrast, highly skilled workers are more competitive in the job market, enjoying greater opportunities and higher salaries. This trend further widens the income gap between high- and low-skilled workers[5].

Thus, the following hypothesis is proposed: H2: The digital economy has a positive impact on high-tech employment but a negative impact on low-tech employment.

3.3. Model Setup

Based on a review of the existing literature, this study selects "total employment at year-end for each province and city" as the measure for employment scale (pep). Employment structure is divided into high-tech and low-tech employment. High-tech employment refers to jobs that involve high technology, such as those requiring computer algorithms or extensive data processing. Low-tech employment refers to all other types of jobs. Since the technical intensity required for different positions varies across industries and even within the same company, the overall educational attainment in China serves as a representative measure. Higher educational attainment generally corresponds to employment in higher-tech roles, while lower educational attainment corresponds to employment in lower-tech roles. Therefore, this study classifies employment based on the level of education.

Table 2: Variable Settings for the Regression Model

	Variable	Meaning	Representation	Data Source
Dependent Variable	pep	Employment Scale	Total Number of Employees at Year-End	China Labor Statistical Yearbook
	LL	Scale of Low-Skill Workers	Employed Population with High School Education or Below	
	HL	Scale of High-Skill Workers	Employed Population with College or Graduate Education	
Core Variable	dige	Measure of Digital Economic Development	Previously Obtained Digital Economic Measures for Various Provinces and Cities	The data measured above
Control Variables	GDP	Regional Economic Development Level	Per Capita GDP in the Region	National Bureau of Statistics
	odr	Degree of Population Aging	Elderly Dependency Ratio	
	trade	Trade Openness	Proportion of Total Imports and Exports to GDP	
	edu	Intensity of Education Investment	Proportion of Provincial Fiscal Education Expenditure to GDP	

3.4. Model Establishment

To empirically examine the impact of the digital economy on overall employment scale, this study sets up a regression model as follows:

$$pep = \alpha + \beta_1 \text{dige} + \beta_2 GDP + \beta_3 odr + \beta_4 trade + \beta_5 edu + \varepsilon \quad (1)$$

Additionally, separate models are established to analyze the effects on high- and low-technology-density employment.

High-technology-density model:

$$\ln HL = \alpha + \beta_1 \text{dige} + \beta_2 GDP + \beta_3 odr + \beta_4 trade + \beta_5 edu + \varepsilon \quad (2)$$

Low-technology-density model:

$$\ln LL = \alpha + \beta_1 \text{dige} + \beta_2 GDP + \beta_3 odr + \beta_4 trade + \beta_5 edu + \varepsilon \quad (3)$$

3.4.1. Descriptive Statistical Analysis

This study primarily uses panel data from 30 provinces and cities in China from 2012 to 2022 (excluding Tibet, Hong Kong, Macau, and Taiwan) for statistical analysis. The descriptive statistics of each variable are shown in the following table:

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Table 3: Descriptive Statistical Analysis of Main Variables

VARIABLES	N	mean	sd	min	max
id	330	15.50	8.669	1	30
year	330	2,017	3.167	2,012	2,022
dige	330	0.240	0.182	0.0490	1
pep	330	575.7	406.9	61.70	2,111
LL	330	449.06	322.50	48.17	1687.29
HL	330	126.68	116.64	9.62	568.05
GDP	330	60,647	30,803	18,947	189,988
odr	330	15.91	4.373	8.800	28.80
trade	330	0.295	0.302	0.00798	1.548
edu	330	0.0410	0.0143	0.0213	0.112
lnpep	330	6.103	0.771	4.122	7.655
lnLL	330	10.46	0.771	8.480	12.04
lnHL	330	9.073	0.895	6.869	10.95

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

The data used in this study are sourced from various statistical yearbooks. The table above presents the descriptive statistics results. It shows that all variables have 330 observations. The mean value for employment scale is 5.757 million people, with a standard deviation of 4.069 million. The minimum and maximum values are 617,000 and 21.11 million people, respectively. In terms of employment skill structure, labor is divided into high- and low-technology-density workers. The mean value for high-tech employment is 1.2668 million, with a minimum value of 96,200 and a maximum of 5.6805 million people. The mean value for low-tech employment is 4.4906 million, with a minimum of 481,700 and a maximum of 16.8729 million people. The overall trend shows that low-tech employment exceeds high-tech employment, indicating that jobs with lower technological demands tend to absorb a larger portion of the workforce.

Regarding the core explanatory variable, the comprehensive digital economy index, the average value is 0.24, with a large range between the minimum and maximum values. This suggests significant differences in digital economy development between regions.

3.4.2. Empirical Results Analysis

This study applies a regression analysis model to estimate the macro-level data. The logarithms of total employment, low-education employment, and high-education employment are taken, and the digital economy is used as the independent variable for the regression.

Table 4: Baseline Regression Analysis Results

VARIABLES	lnpep	lnHL	lnLL
dige	1.276***	2.952***	0.522***
	(8.78)	(18.58)	(3.14)
Constant	5.796***	8.363***	10.331***
	(105.55)	(147.22)	(181.28)
Observations	330	330	330
R-squared	0.090	0.360	0.015

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

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Through regression analysis involving only the independent and dependent variables, it is found that for every 1-unit increase in the comprehensive digital economy index, the total employment increases by 1.276 percentage points. The results show that the growth of the digital economy has a positive effect on both high- and low-technology-density employment. However, the coefficient for high-tech employment is 2.952, which is higher than the 0.522 for low-tech employment.

The results indicate that the development of the digital economy generally benefits employment growth, particularly for high-technology-density jobs. The expansion of the digital economy is expected to create more technical positions, further supporting the growth of high-tech employment.

Table 5: Regression Analysis Results with Control Variables

VARIABLES	lnpep	lnLL	lnHL
dige	0.436***	-0.937**	0.299***
	(1.12)	(-2.33)	(0.84)
GDP	0.000**	-0.000***	0.000**
	(2.32)	(-3.58)	(2.13)
odr	0.014	0.011	0.020**
	(1.44)	(1.12)	(2.35)
trade	0.856***	0.886***	0.803***
	(4.67)	(4.65)	(4.75)
edu	-35.272***	-38.210***	-29.831***
	(-12.72)	(-13.27)	(-11.69)
Constant	7.477***	12.280***	9.416***
	(32.60)	(51.55)	(44.60)
Observations	330	330	330
R-squared	0.521	0.483	0.699

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

The study found that for every 1-unit increase in the digital economy index, the proportion of low-technology-density jobs decreases by 0.0937. The reason for this decline is that jobs characterized by high repetition, physical labor, and danger can be effectively replaced by the digital economy, particularly by artificial intelligence. For example, machines can take over such tasks, leading to optimization and reduction in low-tech employment. Consequently, the substitution effect of the digital economy on low-tech jobs outweighs its job-creating effect.

In contrast, for high-technology-density jobs, the digital economy has the opposite effect. For positions that require advanced technical skills, the development of the digital economy actually stimulates employment growth. An increase of 1 unit in the digital economy index results in a 0.299 proportion increase in high-tech jobs. This suggests that the development of the digital economy enhances production efficiency, enabling more resources to be allocated to research and innovation departments. Furthermore, the rise of high-tech enterprises, driven by the digital economy, attracts more highly educated professionals, indicating that the creation effect of the digital economy on high-tech employment surpasses its substitution effect.

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3.5. Robustness Test

To test the feasibility of the digital economy index, this paper applies principal component analysis (PCA) to re-evaluate the digital economy index. The newly derived index is then substituted into the regression equation to observe whether the regression results remain consistent.

Table 6: Regression Results Using Principal Component Analysis

VARIABLES	lnpep	lnLL	lnHL
dige2	1.442***	-2.155**	1.155***
	(1.56)	(-2.24)	(1.36)
GDP	0.000	-0.000**	0.000
	(1.39)	(-2.58)	(1.21)
odr	0.022**	0.025***	0.014*
	(2.33)	(2.62)	(1.67)
trade	0.705***	0.583***	0.911***
	(4.62)	(3.67)	(6.48)
edu	-34.036***	-36.494***	-30.843***
	(-11.69)	(-12.04)	(-11.51)
Constant	8.018***	13.072***	8.979***
	(18.69)	(29.27)	(22.74)
Observations	330	330	330
R-squared	0.523	0.483	0.700

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

From the table, it can be seen that using PCA to recalculate the comprehensive digital economy index confirms the robustness of the model. The trends in overall employment, as well as high- and low-technology-density employment, are consistent with the results obtained using the entropy method. Specifically, the digital economy positively promotes overall employment, weakens demand for low-tech jobs, and enhances demand for high-tech jobs.

However, the coefficients for the digital economy's impact derived from PCA are generally larger than those from the entropy method. This discrepancy is due to the differences in the principles underlying the two methods, and it does not significantly affect the overall conclusions.

4. Conclusion

4.1. Overall Employment Analysis

The regression coefficient for overall employment is 0.436, indicating that for each unit increase in the digital economy index, total employment increases by 0.436%. Although the substitution effect of the digital economy may have some negative impact on the labor market, the job opportunities created far outweigh the jobs displaced. While advanced technologies, such as artificial intelligence, have replaced certain traditional roles, they have also created entirely new fields and job opportunities. This technological progress not only drives industrial upgrading but also offers more diverse and higher-quality employment opportunities for the workforce.

Regarding control variables, trade openness (trade) has a positive impact on overall employment, with a regression coefficient of 0.856, which is significant. This indicates that China’s foreign trade has provided numerous job opportunities domestically. Additionally, the coefficient for low-technology-density employment is 0.886, which is relatively higher than the 0.803 coefficient for high-technology-density employment. This suggests that education investment intensity (edu) is

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correlated with employment structure, with lower skill employment showing lower values, while higher skill employment is relatively higher.

4.2. Low-Technology-Density Employment Analysis

For low-technology-density jobs, which typically do not require higher education, the number of job opportunities decreases as the digital economy grows. This is because jobs that involve high repetition, physical labor, and hazardous tasks can be effectively replaced by the digital economy, particularly through artificial intelligence, where machines can take over such work. Additionally, the widespread application of big data has simplified information transmission and increased information access efficiency, which, in turn, reduces the demand for manual labor that was previously necessary due to information asymmetry. The rapid development of the digital economy optimizes various industries by enhancing data sharing and reducing the need for such low-tech jobs.

4.3. High-Technology-Density Employment Analysis

In contrast, the development of the digital economy promotes employment in high-technology-density jobs. As the digital economy continues to grow, more high-tech enterprises emerge and expand, requiring more high-skilled talent to support their operations. The tertiary sector, particularly industries related to computing, telecommunications, and software services, tends to be positively affected by the digital economy. These sectors not only need talent to leverage artificial intelligence to improve business efficiency but also require highly skilled professionals to continuously update digital infrastructure and services to better serve societal production needs. Consequently, the demand for high-technology-density employment increases in tandem with the development of the digital economy.

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