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Micro Study on the Impact of the Digital Economy on Income from the Perspective of Labor Matching

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Abstract: As the digital economy continues to develop, the socio-economic structure and lifestyle have undergone significant changes, which have had a profound impact on the labor market. To explore the mechanism of the digital economy's impact on income, this study builds a personal panel data model from a micro perspective and conducts an empirical analysis. The matching situation of individuals in terms of employment and income is assessed through the "skill-job" matching degree and "skill-income" matching degree. A bidirectional fixed-effects model is used for calculation and analysis, comprehensively considering individual characteristics, skill levels, job requirements, and other factors. This study examines the direct and indirect effects of the digital economy on income and explores its influencing mechanisms.

Keywords: digital economy, employment, income, labor matching

1. Introduction

At present, the digital economy is booming, and many new digital economy industrial chains have emerged. The rapid development of related industries has brought about changes in the socio-economic structure and lifestyle, moving people beyond traditional modes of production. This has posed higher demands on the heterogeneous labor force.

How the digital economy affects labor income has become a focal point of attention. This paper takes a micro perspective, focusing on using labor matching indicators to assess the impact of the digital economy on individual income. Data from 31 provincial-level administrative regions across the country from 2010 to 2020 were collected. The "skill-job" matching degree and "skill-income" matching degree were used to evaluate individuals' matching situation in terms of employment and income. A personal panel data model was constructed to study the direct and indirect effects of the digital economy on individual employment and income.

2. Research Hypotheses

2.1. The Digital Economy Directly Affects Income

The rapid development of the digital economy has allowed many to reap its benefits, with numerous studies suggesting that it leads to income disparities at different levels. Scholars largely agree that digital technology can increase the income of both urban and rural residents but argue that varying degrees of impact on urban and rural areas can widen the income gap [1]. Since digital technology can replace highly repetitive and programmable tasks, many physical labor jobs are being supplanted, resulting in a premium on cognitive skills. Female labor, which predominantly involves cognitive-related skills rather than physical labor, thus gains more income, reducing the gender income gap [2]. The phenomenon of employment "polarization" has spread from manufacturing to services and from developed to developing countries [3], widening the income gap between high-skill and low-skill workers. Meanwhile, the impact of technological progress on labor income shares varies significantly across industries [4], with traditional industries experiencing a decline in labor income shares while emerging industries show an inverted "U" shaped increase in labor income shares [5].

2.2. The Digital Economy Affects Income by Influencing Employment

Digital technology has introduced structural contradictions in China's labor market, leading to mismatches between labor supply and demand during employment, which in turn affects income. Many new jobs have emerged with continuous technological progress, greatly increasing labor demand [6]. Research from the perspective of industrial structure concludes that the evolution of industrial structure and the flow of labor across industries are key factors influencing the distribution of labor income in China [7].

3. Analysis of "Skill-Employment-Income" Matching

3.1. Construction of Key Indicators

3.1.1. Labor Skill Structure

At the micro level, there are differences in the labor levels of individuals, such as varying skills and work efficiencies. The labor skills in a provincial administrative region are defined as the average skill level of all laborers in that province.

Based on sample classification methods, laborers' educational levels are categorized into low skill level, medium skill level, and high skill level, with corresponding values assigned. The higher the value, the more the labor structure leans towards being high-skill dominated.

3.1.2. Employment Position Structure

Using job analysis, all positions are classified into five levels, with values assigned as follows: low-income positions—1, lower-middle-income positions—2, middle-income positions—3, upper-middle-income positions—4, and high-income positions—5. This generates an indicator for the hierarchy of employment positions.

3.1.3. Income Structure

Drawing from job analysis, labor income is divided into five levels, with values assigned as follows: low-income group—1, lower-middle-income group—2, middle-income group—3, upper-middle-income group—4, and high-income group—5. This generates an indicator for the hierarchy of labor income.

3.2. Matching Calculation Methods and Results

3.2.1. Matching Calculation Methods

Based on the matching logic of labor quality structure, job structure, and income structure, the higher the level of the labor quality structure, the higher the corresponding job structure level should be, and similarly for the income structure. That is, the higher an individual's labor skill level, the more likely they are to match with high-income positions, thereby increasing their income. Drawing from sociological literature discussing educational matching in marriage, the hierarchical matching method is used to construct the matching degree between each pair [8]. Using the standard ranking matching method, we construct the matching degree by first assigning levels to the labor quality structure as std(labor), job structure as std(job), and income structure as std(income). The differences between each pair are then calculated to obtain the matching degree, as shown in formulas (1), (2), and (3). Based on permutations and combinations, we can obtain three different matching degrees.

$$match1 = std(job) - std(labor) \tag{1}$$

$$match2 = std(job) - std(income) \tag{2}$$

$$match3 = std(income) - std(labor) \tag{3}$$

3.2.2. Results of Different Matching Degrees

The results of various matching degrees are shown in Table 1. Based on the data in the table, we can draw the following analysis and trends:

The "skill-job" matching degree shows relatively small fluctuations overall, with the average value being negative. This indicates that high-skilled individuals often occupy job positions that are lower than their skill levels. From 2010 to 2020, the "job-income" matching degree exhibits larger fluctuations. Although it is sometimes positive, the average value is relatively small, implying that workers in high-income positions have actual income levels that are relatively low and do not match the job levels.

Over the decade, the “skill-income” matching degree shows a slight fluctuation trend, but the average value is negative, indicating that high-skilled individuals generally have relatively low-income levels.

Overall, the absolute values of the three matching degrees are relatively small, suggesting a higher overall matching degree between skills, employment, and income. However, high-skilled individuals are typically employed in relatively low-income positions, and their actual income levels are also lower. Additionally, the actual income levels of workers in high-income positions are relatively low and do not match the job levels. This may be due to structural issues in the current labor market, such as mismatches between skill demand and employment opportunities, as well as unreasonable salary distribution.

Table 1. Average Matching Degrees of National Labor Force from 2010 to 2020

	2010	2012	2014	2016	2018	2020
Skill-Job Matching Degree	-0.0002	-0.0931	0.0000	-0.0003	-0.0005	-0.0004
Job-Income Matching Degree	0.1141	0.0167	-0.0410	-0.1348	0.0036	0.0145
Skill-Income Matching Degree	-0.0725	0.1745	-0.0904	-0.0854	-0.1025	-0.1070

4. Construction and Testing of the Panel Data Model

4.1. Data Sources

The data in this section are derived from the previously calculated Digital Technology Development Level Index and the CFPS database. This includes statistical data from 31 provinces (municipalities and autonomous regions, excluding Hong Kong, Macao, and Taiwan) for the years 2010, 2012, 2014, 2016, 2018, and 2020.

4.2. Variable Selection

4.2.1. Dependent Variable

“Skill-Income” Matching Degree. The “skill-income” matching degree is positively correlated with labor income. High-skilled workers are more competitive in the labor market; they usually possess broader knowledge and skills, can provide higher levels of job performance and value, and are capable of handling more complex and higher value-added jobs, thereby increasing personal income. Based on the results of previous calculations, this paper uses the “skill-income” matching degree to reflect individual labor income, denoted as match3.

4.2.2. Independent Variable

Digital Technology Development Level Index. The Digital Technology Development Level Index is calculated to assess individual digital economic development, with the provincial index being applied to individuals. The individual index values for the same year and province are identical, denoted as dtd.

4.2.3. Mediating Variable

“Skill-Job” Matching Degree. The “skill-job” matching degree refers to the consistency and degree of match between an individual’s skills and the job they perform, denoted as match1.

4.2.4. Control Variables

Gender (gender): A binary variable where 1 represents male.

Household Registration Status (household): A binary variable where 0 represents rural household registration.

Age (age): Sorted by natural age.

Marital Status (marriage): A binary variable where 1 represents married. Respondents indicating married or remarried are categorized as married, while unmarried, cohabiting, divorced, and widowed respondents are categorized as unmarried based on survey questionnaire options.

Industry Classification (industry): According to the classification method in Chapter 4, Primary Industry = 1, Secondary Industry = 2, Tertiary Industry = 3.

Regional Classification (region): According to the classification method in Chapter 4, Western Region = 1, Central Region = 2, Eastern Region = 3.

Low Skill Level (low_skill): According to the classification method in Chapter 4, assigned a value of 1 if the individual belongs to the low skill level, otherwise 0.

Medium Skill Level (mid_skill) and High Skill Level (high_skill) are defined similarly to low skill level.

5. Construction and Testing of Panel Data Model

5.1. Construction of Panel Data Model

To verify the impact of the digital economy on individual labor income and its related pathways, this section constructs a parameter panel data model:

$$match1_{it} = \alpha_0 + \alpha_1 dtd_{it} + \varepsilon_{it} \tag{1}$$

$$match2_{it} = \alpha_0 + \alpha_1 dtd_{it} + \varepsilon_{it} \tag{2}$$

$$match3_{it} = \alpha_0 + \alpha_1 dtd_{it} + \varepsilon_{it} \tag{3}$$

$$match3_{it} = \alpha_0 + \alpha_1 dtd_{it} + \alpha_2 match1_{it} + \varepsilon_{it} \tag{4}$$

$$match3_{it} = \alpha_0 + \alpha_1 dtd_{it} + \alpha_2 match1_{it} + \alpha_3 control_{ijt} + \varepsilon_{it} \tag{5}$$

Here, i represents provinces, t represents years, dtd_{it} is the Digital Technology Development Index, $match3_{it}$ is the “skill-income” matching degree, $match1_{it}$ is the “skill-job” matching degree, $control_{ijt}$ represents a series of control variables, α_0 is the intercept, and ε_{it} is the residual term.

5.2. Panel Data Model Testing and Selection

Based on a static short panel data of 33,598 samples nationwide from 2010 to 2020, covering micro indicators such as digital technology development level, matching degrees, gender, age, marital status, and household registration type, a thorough exploration was conducted. From a micro perspective, individual and time differences were rigorously tested. Statistical tests showed significant individual and time factors ($P < 0.05$), thus a two-factor model was chosen to comprehensively capture individual and time characteristics.

Furthermore, the Hausman test was employed to determine whether to select a fixed effects model or a random effects model. The test results showed a P-value less than 0.05, strongly rejecting the null hypothesis, guiding the selection of a fixed effects model as the more appropriate analytical tool. Considering these analyses, a bidirectional fixed effects model was ultimately selected for in-depth micro data analysis.

5.3. Benchmark Regression Estimation Results and Factor Analysis

Gradually incorporating the digital technology development index, matching degree, and control variables for regression, the results are shown in Table 2.

5.3.1. Direct Impact of the Digital Economy on Employment

Results in columns (1) and (3) of Table 2 indicate that when only the Digital Technology Development Index is included, it significantly affects the “skill-job” matching degree positively and significantly affects the “job-income” matching degree negatively. Columns (2) and (4) show that after adding control variables, the direction and significance of the Digital Technology Development Index’s impact on “skill-job” matching degree remain unchanged, while its impact on “job-income” matching degree changes from negative to positive but becomes insignificant. This suggests that the digital economy affects “skill-employment-income” matching at the individual labor level and significantly promotes employment.

5.3.2. Direct Impact of the Digital Economy on Income

Columns (5) and (6) of Table 2 show that when only the Digital Technology Development Index is included, it significantly promotes the “skill-income” matching degree. Even after adding control variables, this positive impact remains significant, indicating that the level of digital technology development is a key factor in promoting “skill-income” matching, implying that the development of the digital economy can enhance individual labor income.

5.3.3. Analysis of the Impact of the Digital Economy on Labor Income through Employment

In the intermediate model results in columns (7) and (8), the "skill-job" matching degree has a significant positive impact on the "skill-income" matching degree. Even after adding control variables, the results remain significantly positive, suggesting that the digital economy may enhance labor income by promoting employment.

5.4. Analysis of Control Variables

Gender and household registration type show no significant impact on labor income. Age, marital status, and region all show significant positive impacts on labor income. Different skill levels have significant impacts on labor income: low skill levels promote "skill-income" matching, while medium to high skill levels have inhibitory effects. The higher the skill level, the stronger the inhibitory effect.

Table 2. Benchmark Regression Results of the Impact of Digital Technology Development Index on Labor Income (Left Part)

	(1) match1	(2) match1	(3) match2	(4) match2
dtd	0.4035***	0.4335***	-0.5771***	0.1959
	(6.5519)	(4.9777)	(-6.7604)	(1.5110)
match1				
gender		-0.1595		-0.2385
		(-1.2084)		(-1.0719)
age		0.0024		-0.0259***
		(1.1785)		(-9.2562)
household		-0.0031		-0.0146
		(-0.1003)		(-0.3551)
marriage		0.0559**		-0.1839***
		(2.5042)		(-5.5941)
industry		0.2186***		0.2693***
		(15.5613)		(14.0714)
low_skill		0.5762***		0.1404***
		(8.9834)		(7.9659)
mid_skill		-0.6101***		0.0884***
		(-9.2398)		(3.2097)
high_skill		-1.7636***		-0.1536***
		(-24.3148)		(-5.1717)
region		-0.0397*		-0.1862***
		(-1.7632)		(-5.3702)
Individual Fixed Effects	Control	Control	Control	Control
Constant	-0.0628***	-0.4003***	0.1133***	1.0051***
	(-5.0779)	(-2.9914)	(6.9796)	(5.1938)
Observations	47678	45016	37058	35037
R^2	0.670	0.701	0.536	0.550
Adjusted R^2	0.508	0.551	0.284	0.297
F	42.9270	246.8938	45.7027	43.5636

Note: ***, **, * denote significance levels of 1%, 5%, and 10%, respectively.

Table 2. Right Part

	(5) match3	(6) match3	(7) match3	(8) match3
dtd	0.9334*** *	0.3623***	0.8613***	0.2967***
	(12.5363)	(3.4518)	(11.9341)	(2.8480)
match1			0.2063***	0.1145***
			(25.5321)	(14.3576)
gender		-0.0528		-0.0354
		(-0.2462)		(-0.1650)
age		0.0231***		0.0233***
		(10.2933)		(10.5253)
household		0.0295		0.0279
		(0.8652)		(0.8282)

Table 2. Right Part Continued

marriage		0.2810***		0.2717***
		(9.5541)		(9.3288)
industry		0.0089		-0.0168
		(0.5415)		(-1.0282)
low_skill		0.5447***		0.4886***
		(7.5002)		(6.8035)
mid_skill		-0.6545***		-0.5695***
		(-8.9920)		(-7.9087)
high_skill		-1.6198***		-1.4076***
		(-21.0560)		(-18.1731)
region		0.1333***		0.1417***
		(4.4145)		(4.7110)
Individual Fixed Effects	Control	Control	Control	Control
Constant	-0.2842***	-1.3269***	-0.2514***	-1.3148***
	(-18.9822)	(-7.3652)	(-17.2501)	(-7.3171)
Observations	27396	25434	27396	25434
R^2	0.763	0.795	0.774	0.798
Adjusted R^2	0.619	0.666	0.637	0.671
F	157.1577	189.7000	416.3087	197.1171

Note: ***, **, * denote significance levels of 1%, 5%, and 10%, respectively.

5.5. Robustness Tests

To ensure the reliability of the empirical results regarding the impact of digital economic development on “skill-income” matching, robustness tests were conducted using alternative explanatory variables.

Previously, the level of digital technology development was reflected using the Digital Technology Development Index. Here, it was replaced with a binary variable “internet usage” from the CFPS database. If an individual uses the internet (including both computer and mobile internet), it is assigned a value of 1, denoted as internet. According to the regression results in Table 3, after controlling for year effects, individual effects, and other variables, the regression results show that whether an individual uses the internet has a significant positive impact on “skill-job” matching and “job-income” matching, consistent with the previous estimates, confirming the robustness of the model.

However, the impact on “skill-income” matching is significantly negative. This could be because internet usage can indicate an individual’s ability to access digital technology, but due to individual differences, some workers may view “internet usage as a leisure activity,” so “internet usage” does not necessarily improve personal digital skills and may occupy personal free time or even work time, reducing work efficiency and thus lowering labor income.

6. Conclusion

This study, from a micro perspective, focuses on using labor matching indicators to assess the impact mechanism of digital economy on individual income. By constructing individual panel data and applying a two-way fixed effects model for calculation and analysis, the study investigates the direct and indirect effects of the digital economy on individual employment and income, considering factors such as individual characteristics, skill levels, and job demand, and explores the impact mechanism of the digital economy on the job market and personal income.

The research findings indicate that the digital economy significantly affects the “skill-job-income” matching at the individual level. Specifically, the development level of digital technology significantly promotes “skill-income” matching. Therefore, the development of the digital economy can increase income at the individual level. Furthermore, the study meticulously analyzes the heterogeneous effects of skill levels, industries, regions, and household registration types, revealing the differentiated impact of digital economic development on different groups.

Overall, this study delves into the impact mechanism of the digital economy on individual income from a micro perspective. Against the backdrop of rapid digital economic development, governments and relevant departments need to adopt targeted policies and measures to promote the healthy development of the labor market, ensuring that all segments of the population can benefit from the growth of the digital economy. Through in-depth analysis at the individual level, this study supplements macrolevel thinking and provides a more detailed and comprehensive understanding of how the digital economy influences income markets by affecting labor employment.

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