Digital Economy, Declining Demographic Dividend and Rights of Low- and Medium-Skilled Workers

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In the context of the digital economy and the decline in the demographic dividend, how have the rights of low- and medium-skilled workers changed? This study uses cross-sectional data from the China Household Income Project (CHIP) in 2002, 2007, 2008, and 2013, employing a two-way fixed effects model to answer the research question. The findings are as follows: First, the development of the digital economy has reduced the relative income rights of low- and medium-skilled workers but improved their relative welfare. Second, the efficiency gains and industrial intelligence resulting from the digital economy's factor reorganization and reallocation have weakened the relative income rights of low- and medium-skilled workers, but they have enhanced their relative welfare through digital governance models. Third, the labor shortage effect due to the decline in the demographic dividend primarily affects low- and medium-skilled workers, particularly those with low skills, leading to a supply trap. Fourth, in the context of declining demographic dividends, the development of the digital economy has only diminished the rights of low-skilled workers. This suggests that the substitution effect of low-skilled labor caused by the digital economy far outweighs the labor shortage effect due to the decline in the demographic dividend, and the impact of individual endowments, macroeconomic conditions, and government governance levels on the rights of low-skilled workers varies significantly.

Keywords: digital economy, declining demographic dividend, rights and interests of low-and medium-skilled workers

1. Introduction

The digital economy is a new strategic organizational form that leads the new round of technological and industrial revolutions. Accelerating the development of the digital economy is crucial for China to seize the decisive point in this new wave of technological and industrial revolution. Currently, the global digital economy is thriving.

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According to data from the China Academy of Information and Communications Technology (2020), the share of the digital economy in China's GDP has been increasing annually, rising from 14.2% in 2005 to 36.2% in 2019, making it a key driver for transforming China's economic growth model and optimizing its economic structure. However, China faces significant challenges due to the decline in the demographic dividend, including the Lewis trap, aging trap, and low birth rate trap. Data from the National Bureau of Statistics shows that the proportion and number of working-age population have been declining since 2010 and 2013, respectively. In 2019, the proportion of people aged 65 and over reached a new high of 12.6%, while the birth rate was only 10.48 per thousand. On the one hand, the digital economy, characterized by artificial intelligence, big data, cloud computing, 5G technology, industrial internet, and blockchain, accelerates the deep integration of modern information networks and digital technologies with the real economy. This integration unleashes the potential of new business forms, organizations, and models, and significantly enhances the government's digital governance capabilities. On the other hand, it leads to the reorganization of elements and resources by machines, which fundamentally means the redistribution of income. Then, while the digital economy drives economic growth, will it lead to the widening of income gap through the efficiency change caused by the recombination and upgrading of factors and the industrial intelligent and digital governance model? How will the dual macro environment of digital economy development and declining demographic dividend affect the income distribution effect?

According to the existing literature, the income distribution effect of digital economy is mainly reflected in the efficiency change and industrial intelligence orientation caused by the recombination and upgrading of factors and the redistribution, as well as the path dependence and value choice of digital governance mode in dynamic game. Specifically:

Firstly, from the perspective of upgrading and reconfiguring elements and transforming efficiency, this is primarily reflected in the digital economy's role in complementing and substituting capital and labor, or in the technological expansion of these factors, ultimately driving efficiency improvements. First, from the perspective of the technological bias of information technology or artificial intelligence, numerous studies suggest that the technological revolution, represented by the digital economy, has significantly enhanced the efficiency of capital accumulation, while decreased the comparative advantage of labor. In the labor market, this is more evident in machines replacing humans, leading to widespread unemployment (Acemoglu and Restrepo, 2020; Wang *et al.*, 2020). However, the integration of the digital economy with the real economy may only replace a portion of the workforce in specific economic environments. Information technology can also serve as an intermediary to enhance labor productivity, not necessarily substituting capital for labor, especially in high-tech, intensive, and precise labor scenarios (He *et al.*, 2019). Therefore, information technology and artificial intelligence primarily improve the allocation efficiency of capital and labor, enhancing the degree to which machines can replace human labor (Hjort and Poulsen, 2019). Additionally, some scholars view information technology and artificial intelligence as capital-expanding technologies (Graetz and Michaels, 2018) or labor-expanding technologies (Bessen, 2018). The digital economy does not absolutely replace capital or labor but rather determines the relative replacement of capital or labor based on allocation efficiency (Agrawal *et al.*, 2019).

Secondly, from the perspective of factor reorganization and upgrading, reconfiguration, and industrial intelligence, the reorganization and upgrading of factors lead to a gradual shift of capital and labor towards the service sector, where productivity growth is relatively slower. This results in a decline in the share of manufacturing, which has higher productivity growth, in GDP, while the share of the service sector, which has slower productivity growth, increases in the national economy. This phenomenon is known as the "Baumol's disease" effect (Baumol, 1967). Compared to traditional infrastructure, new infrastructure, such as the digital economy, has a higher investment ratio in the service sector (Guo *et al.*, 2020). The deep integration of the digital economy with the real economy is primarily reflected in the rapid advancement of digital industrialization and industrial digitalization, including artificial intelligence, 5G, big data, cloud computing, industrial internet, and blockchain. These industries are part of the service sector, which is led by industrial intelligence. Therefore, in the context of the digital economy, the market position of the service sector, guided by industrial intelligence, is gradually rising. In the current context of declining demographic dividends, the digital economy's impact on industrial structure selection is more evident in the deep integration of machines and manufacturing, which reduces the cost burden of manufacturing production and enhances its market capacity. Under conditions of limited market demand, the market position and tradability of manufacturing are gradually diminishing, leading to a gradual shift of surplus labor to the service sector. The intangible, non-physical, and low-energy consumption characteristics of the service sector naturally complement the high efficiency of artificial intelligence, big data, and blockchain, fostering the disruptive development of modern services.

Thirdly, in terms of digital governance models, it involves properly managing the relationship between the growth effects of the digital economy and inclusive growth. As a new form of economy characterized by new organizations, models, and business forms, the digital economy integrates and allocates capital and labor resources, optimizes and upgrades industrial intelligence, ultimately leading to quality, efficiency, and power transformations that impact overall social income distribution. The development of the digital economy, particularly in the realm of artificial intelligence, originates from market operations. Many scholars argue that digital governance can enhance information transparency, reduce transaction costs, improve the institutional environment, and promote more equitable social income distribution (Lindstedt and Naurin, 2010; Zhao *et al.*, 2019). Therefore, the government should leverage digital governance platforms to use digital technology to modernize its governance capabilities and enhance the efficiency of implementing inclusive growth strategies.

At the same time, our country is facing significant challenges due to the disappearance of the demographic dividend caused by population structure traps such as the Lewis trap, aging trap, and low birth rate trap. Cai (2010) argues that the decline in the demographic dividend is primarily due to a shortage of labor supply, particularly among migrant workers, which has led to a substantial increase in their wages. Other studies have examined the economic growth effects of the declining demographic dividend from the perspective of changing factor inputs. On the one hand, the decline in the demographic dividend influences economic growth through the intermediate mechanism of increasing human capital accumulation. In other words, to alleviate labor supply pressure, the efficiency of human capital investment is enhanced (Lee and Mason, 2010). On the other hand, the decline in the demographic dividend influences economic growth through the intermediate mechanism of increasing material capital accumulation. This means that in the context of a declining demographic dividend, increased investment in material capital and improved productivity of material capital are essential (Ma *et al.*, 2016; Tie *et al.*, 2019). Essentially, these two pathways involve changing the input methods of factors, improving the utilization rate of capital, promoting the substitution of capital for labor or the endowment of capital to individuals, and utilizing the recombination of factors to promote economic growth and income distribution.

The above literature offers rich and profound insights into the income distribution effects of digital economic development and the decline in demographic dividends. However, there are two main issues: first, the digital economy is a rapidly evolving concept, and the academia has yet to reach a consensus on how to measure it; second, most existing literature focuses solely on the income distribution effects of the digital economy or the decline in demographic dividends. A few studies have also examined the impact from an aging perspective, suggesting that as the degree of aging increases, companies will increase their investment in artificial intelligence, thereby mitigating the negative economic impacts of aging (Chen *et al.*, 2019). However, no research has explored the impact of digital economic development, the decline in demographic dividends, and their combined effects on the income patterns of individual microeconomic agents, particularly the changes in welfare disparities.

This article proposes three potential innovations: First, the digital economy, as a new strategic organizational form leading the next generation of technological revolution, enhances the efficiency of production, exchange, distribution, and consumption through its integration with the real economy, thereby reducing transaction costs. This paper examines the evolution of income distribution and welfare levels for workers with different skills under the dual macroeconomic backdrop of the development of the digital economy and the decline in the demographic dividend, offering a new perspective on understanding the current disparities in skill-based income distribution. Second, the paper delves into the mechanisms by which the digital economy affects income distribution, considering factors such as efficiency changes due to the reorganization and upgrading of factors, industrial intelligence, and digital governance levels. This analysis provides policy implications for balancing the income distribution effects of the digital economy with inclusive growth. Third, drawing on the definitions and variable handling methods of the digital economy from the China Academy of Information and Communications Technology (2020) and Zhao *et al.* (2020), this article measures the digital economy through the lenses of digital industry activity, digital innovation activity, digital user activity, and digital platform activity. The comprehensive digital economy index differs from existing literature that measures the digital economy from a single dimension.

2. Data Processing and Research Design

2.1. Data Sources

The data in this article are derived from the Urban Household and Migrant Population Household Surveys conducted by the China Household Income Project (CHIP) in 2002, 2007, 2008, and 2013. The study of wage income and welfare income excludes private and individual business owners, retirees, and unemployed domestic workers. Other macro data sources include the CEIC China Economic Database, China Urban Statistical Yearbook, China E-commerce Yearbook, Provincial Input-Output Tables, China Procuratorial Yearbook, China Statistical Yearbook, China Statistical Yearbook for Regional Economy, China Labor Statistical Yearbook, and the Enterprise Research Data-Digital Economy Industry Special Database.

2.2. Variable Specification

2.2.1. The Explained Variable

The rights and interests of workers are divided into two parts: one is wage income, and the other is welfare level.

(1) Log of real annual wage income. In this paper, the logarithm of actual annual wage income of micro-level individuals is taken as the dependent variable of income change. The sample span is about 10 years. In order to ensure the consistency of annual statistical caliber, we take 2002 as the base period, use the consumer price index of each region for deflation and logarithmic processing, and obtain the logarithm of actual

annual wage income.

(2) Welfare level. This paper selects four dimensions related to the welfare level of workers, including whether they have old-age insurance, medical insurance, unemployment insurance, and work injury insurance. A value of 1 indicates the individual has received the corresponding welfare, while 0 indicates no such benefits. Following Qian and Li (2013), the principal component analysis method[1] is used to synthesize these four 0-1 variables into a comprehensive indicator of residents' welfare. Then, using the median dichotomy method, we can get dummy variables for individual welfare levels, where 1 indicates a high welfare level and 0 indicates a low welfare level.

2.2.2. Explanatory Variables

(1) Low- and medium-skilled workers. Most existing literature classifies workers based on their educational background or occupational category using a single indicator (Li and Shao, 2017; Shen *et al.*, 2017). To more comprehensively reflect the differences in social skills among workers, this paper categorizes them into three groups—high, medium, and low—based on both educational background and occupational category. Specifically, workers with 16 years or more of education are classified as having a high level of education, while those with less than 16 years of education are classified as having a low level of education. Workers in high-skilled occupations, such as party and mass organizations in government agencies, leaders of enterprises and institutions, professional and technical personnel, clerical staff, and administrative office managers, are defined as high-skilled workers. The rest are defined as low-skilled workers. Based on this classification, workers with a high level of education and in high-skilled occupations are defined as high-skilled workers, those with a low level of education and in low-skilled occupations are defined as low-skilled workers, and the remaining workers are categorized as medium-skilled workers.

(2) Digital economy. The China Academy of Information and Communications Technology (CAICT) (2020) elucidates the essence of the digital economy from four perspectives: digital industrialization, industrial digitalization, digital governance, and data valorization. Building on this, this paper further draws from Zhao *et al.* (2020) to measure the digital economy through the lenses of digital industry activity, digital innovation activity, digital user activity, and digital platform activity. Digital industry activity primarily encompasses the development level of foundational digital industries, as measured by the proportion of employment in information transmission, computer services, and software, the revenue from software business, and the share of fixed assets in the information transmission, computer services, and software sector. Digital

[1] The KMO test value reached 0.76, which met the conditions of principal component analysis.

innovation activity reflects the level of intelligent technology and digital innovation in the digital economy, measured by the number of 5G industry patents, industrial internet patents, and e-commerce patents. Digital user activity assesses users' digitalization levels and the functions of mobile payments in the digital economy, including the mobile phone penetration rate, total telecommunications business volume, e-commerce transaction volume[1], and the number of per capita Internet broadband access users (Internet broadband access users / permanent population of prefecture-level cities). Digital platform activity highlights the digitalization level of network platforms, calculated using the number of domain names, the number of Internet users, and the number of websites.[2]

This paper aims to use principal component analysis to synthesize the digital economy by integrating the activity levels of the digital industry, digital innovation, digital users, and digital platforms. However, the KMO test value for these four dimensions of the digital economy indicators is only 0.47, which does not meet the necessary conditions for principal component analysis. Therefore, this paper, following Fan *et al.* (2011), applies dimensionless processing to each indicator and uses the arithmetic mean method to synthesize the four dimensions into a comprehensive digital economy.

(3) Urban demographic dividend. Drawing on Bloom and Williamson (1997) and Lu and Cai (2016), the proportion of the working-age population is positively correlated with the demographic dividend. Conversely, the dependency ratios for the elderly, preschool children, and school-age students are negatively correlated with the demographic dividend. The family demographic dividend index is calculated using the arithmetic mean method: Family Demographic Dividend Index = (Proportion of Working-age Population − Dependency Ratio for the Elderly − Dependency Ratio for Preschool Children − Dependency Ratio for School-age Students) / 4. This index is then averaged at the city level to derive the city-level demographic dividend index. In the robustness analysis, the family demographic dividend index is used to replace the city-level demographic dividend index.

2.2.3. Mechanism Variables

(1) Industrial intelligence. Drawing on the measurement of industrial intelligence indicators by Yang and Fan (2020), the degree of industrial intelligence is measured by the proportion of total intermediate inputs from information transmission, computer

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[1] Due to the limitation of data, we can only search for the e-commerce transaction volume data of each province in 2005,2008 and 2013. Therefore, the annual average replacement method is used to supplement the data in 2002 and 2007.

[2] The sub-indicators of the digital economy are not reported in the main text due to space limitations. Interested readers can contact the author for more information.

services and software industry to total added value in each provinces' input-output table.

(2) Regional productivity. This paper draws on Zhang *et al.* (2004) and employs the perpetual inventory method to estimate capital stock. It aggregates the total number of employees in urban units, private, and individual sectors across different regions. Using 2002 as the base year, it adjusts the GDP data of each city over the years to reflect 2002 constant prices. The DEA-Malmquist productivity index for each region is then calculated using DEAP2.1 software. To ensure the robustness of the results, the paper also uses the ratio of actual GDP to capital stock in prefecture-level cities as an indicator of regional capital productivity, serving as a proxy for total factor productivity.

(3) Legal efficiency and regulatory quality. Zhao *et al.* (2019) argue that the development of big data positively impacts the legal system and government oversight. They measure the level of legal system development in a region using the number of law firms per 10,000 people and the number of lawyers per 10,000 people. They also assess the quality of government oversight through the ratio of fire incidents to casualties and the ratio of traffic accidents to casualties. This paper uses these standards to evaluate the efficiency of the legal system and the quality of government oversight.

2.2.4. Other Control Variables

This paper aims to control for key variables from both micro and macro perspectives. At the micro level, it includes the respondents' age, age squared, gender, marital status, education level, health status, and household registration type. The macroeconomic environment is also a significant factor influencing the regression results of this study. For example, the first batch of college graduates entering the labor market after the expansion of higher education admissions in 1999 may have increased the demand for highly skilled workers in various positions; the implementation of the minimum wage system in 2004 led to an increase in the income levels of middle- and low-skilled workers; the global financial crisis in 2008 had a significant impact on labor demand across different regions and industries. To avoid biases in the estimation results caused by these significant events, the paper controls for the ratio of ordinary college graduates to total employment in prefecture-level cities, the logarithm of the minimum wage, and the GDP growth rate. Additionally, it controls for the logarithm of the actual average wage of employees in the region, the ratio of fixed asset investment to GDP, and the success rate of mediation of labor disputes by trade unions.

2.3. Research Methods and Model Setting

In this paper, the model mainly adopts the two-way fixed effect model at the city and time levels. The basic model is set as follows:

$$Y_{irt} = \beta_0 + \beta_1 Llabor_{it} \times Digit_{rt} + \beta_2 Mlabor_{it} \times Digit_{rt} + \beta_3 A + \beta_4 X + \lambda_t + \theta_r + \xi_{irt} \quad (1)$$

Among these, Y_1 represents the logarithm of actual annual wage income (*Realwage)*, Y_2 indicates whether there is a high welfare effect (*Welfare)*, $Digit_{rt}$ denotes the presence of the digital economy, $Llabor_{it}$ indicates whether the workforce is low-skilled, and $Mlabor_{it}$ indicates whether the workforce is medium-skilled. A stands for control variables for the digital economy, dummy of indicating low-skilled labor, dummy of indicating medium-skilled labor, respectively. X represents a set of control variables at the individual (i), city (r) level, and provincial (k) level, with λ and θ representing time and city fixed effects, respectively. The core explanatory variables $Llabor_{it} \times Digit_{rt}$、$Mlabor_{it} \times Digit_{rt}$ in this paper are interaction terms. To avoid bias in estimating interaction coefficients in non-linear probability models (Ai and Norton, 2003), all estimates of the welfare gap in this paper use the OLS linear probability model.[1]

3. Empirical Results and Analysis

3.1. Development of Digital Economy and Rights and Interests of Low- and Medium-Skilled Workers

3.1.1. Baseline Regression Results

Table 1 presents the baseline results of the impact of the digital economy on the rights and interests of low- and medium-skilled workers. Column (1) shows that, under the same conditions, an increase of one unit in the digital economy results in a 36.9% decrease in the actual annual income of low-skilled workers and a 23.1% decrease in the actual annual income of medium-skilled workers, indicating that the digital economy reduces the income rights of low- and medium-skilled workers. Similarly, column (2) indicates that the digital economy enhances the relative welfare levels of low- and medium-skilled workers. Columns (3), (4), (5), and (6) provide individual indicators of welfare levels. Except for column (4), the regression results show that the interaction effect between the digital economy and low- and medium-skilled workers is significantly positive, meaning that the digital economy improves the welfare effects of old-age insurance, unemployment insurance, and work injury insurance for these workers. Therefore, while the development of the digital economy reduces the relative income rights of low- and medium-skilled workers, it also leads to an increase in their relative welfare levels.

[1] Due to space limitations, the descriptive statistics of the main variables are not reported. Interested readers can contact the author for more information.

Table 1. Baseline Regression Results

Variable name	Realwage	Welfare	Old-age insurance	Medical insurance	Unemployment insurance	Work injury insurance
	(1)	(2)	(3)	(4)	(5)	(6)
$Llabor_{it} \times Digit_{rt}$	–0.369*** (0.0645)	0.132*** (0.0421)	0.121*** (0.0407)	0.0508 (0.0476)	0.170*** (0.0502)	0.195*** (0.0555)
$Mlabor_{it} \times Digit_{rt}$	–0.231*** (0.0664)	0.165*** (0.0419)	0.167*** (0.0401)	–0.0574 (0.0456)	0.135*** (0.0521)	0.212*** (0.0576)
$Digit_{rt}$	0.435** (0.212)	0.710*** (0.158)	0.961*** (0.157)	–0.0557 (0.135)	0.162 (0.179)	0.487* (0.2614)
$Mlabor_{it}$	–0.0186 (0.0377)	–0.0217 (0.0266)	0.0223 (0.0254)	0.0387 (0.0226)	–0.0355 (0.0318)	–0.0937*** (0.0352)
$Llabor_{it}$	–0.183*** (0.0378)	–0.0795** (0.0271)	–0.0428* (0.0260)	–0.0628*** (0.0228)	–0.0777** (0.0313)	–0.0909*** (0.0346)
Sample size	32,741	28,100	28,487	33,199	28,203	28,180
R^2	0.461	0.442	0.426	0.170	0.377	0.275

Note: (1) Values in parentheses are robust standard errors; ***, ** and * indicate significance at the 1%, 5%, and 10% level; (2) All regressions include fixed effects for cities and time, with clustering applied at the city level. (3) All regression results control for micro and macro-level covariates, but due to space limitations, these controls are not reported in the main text. The same applies for the tables below.

3.1.2. Robustness Test

(1) Instrumental variable test. On the one hand, the higher the level of regional economic development and the more comprehensive the social security system, the higher the Internet construction and information transparency, which in turn is more conducive to the growth of the digital economy. Therefore, the benchmark model may have an endogenous reverse causality issue. On the other hand, due to data limitations, the digital economy indicators measured above may contain measurement errors. These errors can lead to correlations between the digital economy indicators and unobservable factors affecting workers' wages and benefits, resulting in endogeneity issues in the estimation coefficients of core variables. To address this, it is necessary to find appropriate instrumental variables for testing.

Geographical location and topographic features are exogenous variables that are independent of the economic system. This paper adopts the method of using geographical location and topographic features as exogenous instrumental variables, as suggested by Nunn and Qian (2014). Based on the *National Coastal Port Layout Plan* published by the Ministry of Transport and using Google Maps as a reference, the distances from each prefecture-level city to coastal ports were calculated based on their coordinates. To ensure the time-varying nature of the instrumental variables in terms of both time and cities, this paper follows Nunn and Qian (2014) and uses the number of digital economy enterprises nationwide during the sample period (Num_t) to reflect the time-varying nature of the instrumental variables. Digital enterprises, as key players in the development of the digital economy, are important indicators of the current state of digital economic development. However, these enterprises do not directly affect workers' income and welfare levels but influence income distribution indirectly by affecting the level of digital economic development. Therefore, the interaction effect between the distance to coastal ports and the number of digital economy enterprises nationwide meets the conditions of "strict exogeneity" and "strong correlation". Thus, this paper uses the interaction term between the logarithm of the distance to coastal ports and the logarithm of the number of digital economy enterprises nationwide as a benchmark instrumental variable. To verify the robustness of these conclusions, this paper also considers surface and topographic features, adopting the interaction term between the topographic undulation degree of each region and the logarithm of the number of digital economy enterprises nationwide as an instrumental variable, and re-estimates the basic model.

The results in Table 2 show that the F-statistics for the first stage are all greater than the critical value of 10, indicating a strong statistical correlation between the endogenous and instrumental variables. From an economic perspective, this suggests that the instrumental variables have a strong explanatory power over the endogenous variables. The weak IV test results indicate that the Cragg-Donald Wald F-statistics for each column exceed the critical value at the 10% significance level set by Stock-Yogo, meaning both types of instrumental variables pass the weak instrument variable test. Additionally, the K-Paaprk LM statistics for each column reject the null hypothesis at the 1% significance level, confirming that the instrumental variables meet the identification criterion. Based on the characteristics of the local causal effects of the instrumental variables, the second-stage regression results support the conclusion of the benchmark model: the development of the digital economy has reduced the relative income rights of low- and medium-skilled workers but has improved their relative welfare levels.

Table 2. Regression Results of Instrumental Variable Regression

Explained variable in the first-stage regression: $Digit_{rt}$			
$\ln(Num_t)\times\ln(Dis_r)$	-0.0122^{***} (0.000329)	$\ln(Num_t)\times Slope_r$	-0.0208^{***} (0.000593)
$Llabor_{it}\times\ln(Num_t)\times\ln(Dis_r)$	-0.000105^{**} (0.0000536)	$Llabor_{it}\times\ln(Num_t)\times Slope_r$	0.00000440 (0.000129)
$Mlabor_{it}\times\ln(Num_t)\times\ln(Dis_r)$	-0.000141^{**} (0.0000550)	$Mlabor_{it}\times\ln(Num_t)\times Slope_r$	−0.000104 (0.000128)

Second stage regression results				
	IV: $\ln(Num_t)\times\ln(Dis_r)$		IV: $\ln(Num_t)\times Slope_r$	
Explained variable	*Realwage*	*Welfare*	*Realwage*	*Welfare*
$Llabor_{it}\times Digit_{rt}$	–0.8002*** (0.1657)	0.164** (0.0826)	–0.583*** (0.198)	0.260** (0.127)
$Mlabor_{it}\times Digit_{rt}$	–0.783*** (0.181)	0.207** (0.0858)	–0.519*** (0.204)	0.292** (0.128)
$Digit_{rt}$	0.298 (0.658)	1.546** (0.705)	2.232*** (0.600)	1.419** (0.582)
$Mlabor_{it}$	0.0202 (0.0956)	–0.0692 (0.0488)	0.187* (0.108)	–0.111 (0.0716)
$Llabor_{it}$	0.0381 (0.0888)	–0.0382 (0.0474)	–0.0583 (0.1055)	0.0608 (0.0714)
Partial R^2 (F-statistics of the first stage)	0.0974 (461.102)	0.0486 (105.453)	0.0731 (430.963)	0.0533 (111.427)
Identifiable test <P-value>	780.895 <0.0000>	196.383 <0.0000>	498.144 <0.0000>	130.087 <0.0000>
Weak IV test	1171.706 [22.30]	459.869 [22.30]	852.497 [22.30]	485.006 [22.30]
Sample size	32,741	28,100	32,741	28,100
R^2	0.459	0.441	0.454	0.437

Note: The table above uses the K-Paaprk LM statistic for identification test, with the P-values of the corresponding statistics in parentheses. It also employs the Cragg-Donald Wald F statistic for weak instrumental variable (IV) testing, where the critical values for the Stock-Yogo weak IV test at the 10% significance level are provided in square brackets. Due to space limitations, the regression results with $Llabor_{it}\times Digit_{rt}$ and $Mlabor_{it}\times Digit_{rt}$ as dependent variables were omitted when reporting the first stage results, but are available upon request.

(2) Other robustness tests. The aforementioned empirical analysis process only examined the urban and migrant population samples, meaning we can only observe the urban and migrant population that is part of the labor force, while ignoring the urban population that has not entered the labor market and the rural population that has not migrated or moved to cities. This may introduce a sample selection bias in this study. To address this, this paper uses Heckman's (1974) two-step method to correct for sample selection bias, which still supports the conclusions of the basic model. Additionally, in recent years, the government has introduced numerous policies to ensure the welfare of low-and medium-skilled workers, such as the New Rural Cooperative Medical Scheme and the New Labor Contract Law. This paper further controls for the work injury insurance participation rate, unemployment insurance participation rate, old-age insurance participation rate, and medical insurance

participation rate in various regions, conducting an omitted variable test. This paper also calculates the number of digital enterprises in each province, replacing the comprehensive digital economy indicator mentioned above, all of which support the conclusions of the baseline model.[1]

3.1.3. Mechanism Test

How does the digital economy lead to a decline in income for low-and medium-skilled workers? How does it increase their welfare effects? What are the mechanisms behind these changes? On the one hand, the digital economy enhances production efficiency through the reorganization and reallocation of capital and labor. Since the impact on capital accumulation of the digital economy is greater than that on labor, and high-skilled sectors tend to be capital-intensive while low-skilled sectors are labor-intensive, the digital economy can improve the efficiency of capital-intensive, high-skilled sectors, leading to higher incomes and reducing the relative income rights of low- and medium-skilled workers. On the other hand, the restructuring and upgrading of capital and labor elements in the industrial structure result in a gradual shift of capital and labor elements towards sectors such as information technology, artificial intelligence, big data, cloud computing, industrial internet, blockchain, and 5G technology. These sectors are characterized by an intelligent development model. The development of industrial intelligence accelerates the replacement of human workers by machines, thereby worsening income distribution through job substitution due to industrial intelligence. This indirectly confirms that the digital economy, while replacing low- and medium-skilled positions with intelligent jobs, asymmetrically raises the productivity threshold of different technical sectors, accelerating the erosion of the income rights of low- and medium-skilled workers (Wang *et al.*, 2020).

To this end, this paper first uses total factor productivity (TFP) to measure production efficiency and examines how the digital economy affects workers' income. Given that digital technologies such as information technology, artificial intelligence, big data, cloud computing, industrial internet, blockchain, and 5G technology are capital-intensive in their industrialization and digital transformation, the paper also uses urban capital productivity as a proxy for productivity to further explain the impact. Additionally, it selects indicators of industrial intelligence to examine how the digital economy enhances smart technology, which in turn affects the income gap among workers. Secondly, from the perspective of digital governance models, the paper examines how the digital economy impacts workers' welfare. In recent years, various social security systems have been gradually improved, particularly the policies aimed

[1] Due to space limitations, the results of the above robustness tests are not reported in the main text. Interested readers can contact the author for more information.

at low-skilled workers, which have been progressively implemented. The development of the digital economy has further enhanced the government's legal efficiency and the quality of policy implementation. Therefore, the digital economy, represented by digital governance models, improves the efficiency of policy implementation through the regulation of social welfare policies, thereby enhancing the welfare levels of low- and medium-skilled workers. This paper measures legal efficiency using the number of law firms and lawyers per ten thousand people, and uses the ratio of fire incidents to casualties and traffic accidents to fatalities to assess the quality of government supervision (Zhao *et al.*, 2019), to examine the mechanisms by which the digital economy impacts workers' welfare levels.

In the columns (1), (2), and (3) of Table 3, the interaction coefficients between the digital economy effect on low- and medium-skilled workers and total factor productivity ($Facpro_{rt}$), capital productivity ($Faccap_{rt}$), and industrial intelligence ($Indusintel_{kt}$) are all significantly negative. This indicates that the digital economy, by enhancing production efficiency and industrial intelligence, has worsened the income distribution for low-and medium-skilled workers. In the columns (4), (5), (6), and (7), the interaction coefficients between the digital economy effect on low- and medium-skilled workers and the number of law firms per ten thousand people ($Lawf_{kt}$), the number of lawyers per ten thousand people ($Lawyer_{kt}$), traffic accident supervision quality ($Traffic_{kt}$), and fire supervision quality ($Fire_{kt}$) are all significantly positive. This suggests that the digital economy, by improving legal efficiency and government supervision quality, has enhanced the welfare of low-and medium-skilled workers.

Therefore, the productivity effect and industrial intelligence orientation caused by the recombination, upgrading and redistribution of factors in the digital economy weaken the relative income level of low- and medium-skilled workers, but the digital governance model improves the quality of government supervision and the efficiency of legal system, and improves the relative welfare level of low- and medium-skilled workers.

Table 3. Mechanism Analysis

Explained variable	Realwage			Welfare			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Llabor_{it} \times Digit_{rt} \times Facpro_{rt}$	-2.132^{***} (0.770)						
$Mlabor_{it} \times Digit_{rt} \times Facpro_{rt}$	-1.807^{**} (0.770)						
$Llabor_{it} \times Digit_{rt} \times Faccap_{rt}$		-0.604^{***} (0.231)					
$Mlabor_{it} \times Digit_{rt} \times Faccap_{rt}$		-0.516^{**} (0.230)					
$Llabor_{it} \times Digit_{rt} \times Indusintel_{kt}$			-0.983^{*} (0.540)				

Explained variable	Realwage			Welfare			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Mlabor_{it} \times Digit_{rt} \times Indusintel_{kt}$			–0.971* (0.546)				
$Llabor_{it} \times Digit_{rt} \times Lawf_{kt}$				1.727*** (0.283)			
$Mlabor_{it} \times Digit_{rt} \times Lawf_{kt}$				1.991*** (0.285)			
$Llabor_{it} \times Digit_{rt} \times Lawyer_{kt}$					0.136*** (0.0202)		
$Mlabor_{it} \times Digit_{rt} \times Lawyer_{kt}$					0.175*** (0.0203)		
$Llabor_{it} \times Digit_{rt} \times Traffic_{kt}$						0.552*** (0.0397)	
$Mlabor_{it} \times Digit_{rt} \times Traffic_{kt}$						0.660*** (0.0400)	
$Llabor_{it} \times Digit_{rt} \times Fire_{kt}$							0.000824* (0.000462)
$Mlabor_{it} \times Digit_{rt} \times Fire_{kt}$							0.000900** (0.000438)
$Llabor_{it} \times Digit_{rt}$	1.640** (0.7287)	–0.321* (0.173)	0.547 (0.4769)	0.0215 (0.0657)	0.0444 (0.0636)	0.583 (0.747)	0.156** (0.0611)
$Mlabor_{it} \times Digit_{rt}$	0.0632 (0.726)	–0.233 (0.174)	0.6011 (0.4838)	0.0157** (0.0672)	0.0369 (0.0649)	0.0883 (0.747)	0.0481 (0.0606)
Sample size	32,511	32,549	23,768	27,638	27,638	28,100	28,100
R^2	0.463	0.463	0.474	0.446	0.446	0.443	0.444

3.2. Development of Digital Economy, Decline of Demographic Dividend and Rights and Interests of Low- and Medium-Skilled Workers

3.2.1. The Impact of Declining Demographic Dividend on the Rights and Interests of Low- and Medium-Skilled Workers

If the decline in the demographic dividend is due to a shortage of low-and medium-skilled workers, it will lead to an improvement in the relative benefits of these workers. If the decline is due to a shortage of high-skilled workers, it will improve the relative benefits of high-skilled workers. As shown in columns (1) and (2) of Table 4, the decline in the demographic dividend has led to an increase in the relative income of low- and medium-skilled workers and an improvement in the welfare level of low-skilled workers. However, the effect on the welfare of medium-skilled workers is not significant. Therefore, the decline in the demographic dividend not only increases the relative income of low- and medium-skilled workers but also improves the relative welfare of low-skilled workers. Additionally, comparing the interaction coefficients in columns (1) and (2), it is evident that the decline in the demographic dividend has a greater impact on improving the rights of low-skilled workers. To verify the robustness of these conclusions, columns (3) and (4) used the household demographic dividend index to replace the urban demographic dividend indicator, which largely supports the findings in columns (1) and (2). We speculate that the current labor shortage effect of the declining demographic dividend mainly stems from the supply trap of low- and medium-skilled workers, particularly from the low-skilled workers (Cai , 2010).

Table 4. The Impact of Declining Demographic Dividend on the Rights and Interests of Low- and Medium-Skilled Workers

Explained variable	Realwage	Welfare	Realwage	Welfare
	(1)	(2)	(3)	(4)
	Urban demographic dividend: $Demo_{rt}$		Family demographic dividend $Demo_{ft}$	
$Llabor_{it} \times Demo$	–0.439*** (0.0968)	–0.300*** (0.0610)	–0.0557*** (0.0180)	–0.0769*** (0.0118)
$Mlabor_{it} \times Demo$	–0.328*** (0.0961)	0.0569 (0.0599)	–0.0471** (0.0184)	–0.0271** (0.0121)
$Llabor_{it}$	–0.147*** (0.0524)	0.155*** (0.0335)	–0.379*** (0.0171)	0.0319*** (0.0110)
$Mlabor_{it}$	0.0252 (0.0511)	0.0158 (0.0324)	–0.148*** (0.0155)	0.0527*** (0.00979)
$Demo$	3.789 (2.669)	–4.648** (2.155)	–0.0315* (0.0163)	0.0385*** (0.0104)
Sample size	32,747	28,106	32,508	27,875
R^2	0.460	0.444	0.462	0.445

3.2.2. The Impact of Digital Economy Development and Declining Demographic Dividend on the Rights and Interests of Low- and Medium-Skilled Workers

The analysis shows that the digital economy, through the reorganization and upgrading of factors and their reallocation, has led to efficiency changes and industrial intelligence, which have reduced the relative income rights of low-and medium-skilled workers. However, the development of the digital economy, through digital governance platforms, has improved the government's legal efficiency and policy supervision quality, thereby enhancing the welfare levels of low-and medium-skilled workers. Meanwhile, the decline in demographic dividends, represented by the Lewis trap, aging trap, and low birthrate trap, has resulted in a shortage of low-and medium-skilled labor, particularly the low-skilled labor. Thus, the decline in demographic dividends has also improved the income and welfare levels of low-and medium-skilled workers. Given the dual macroeconomic context of the digital economy's development and the decline in demographic dividends, how have the rights and interests of low-and medium-skilled workers evolved?

As shown in column (1) of Table 5, the interaction term coefficient between the digital economy and the urban population dividend index is significantly positive at the 1% level. The marginal effect of the digital economy on the real income of low-skilled workers ($2.434 \times Demo_{rt} - 1.384$) indicates that, in the context of a declining demographic dividend, the digital economy leads to a greater decline in the income of low-skilled workers. The empirical results in column (2) show that the interaction term coefficient between the digital economy and the urban population dividend index is significantly positive at the 5% level. Solving this equation reveals that, in the context of a declining demographic dividend, the digital economy results in a smaller increase in the welfare effect for low-skilled workers. In summary, in the context of a declining demographic dividend, the digital economy leads to a greater decline in the income of low-skilled workers and a smaller increase in their welfare effect. This means that the digital economy weakens the wage and welfare effects for low-skilled workers. The primary reason is that, in the context of a declining demographic dividend, the shortage of low-skilled labor due to the decline in the demographic dividend improves their rights. However, the shortage of low-skilled labor also accelerates the process of industrial intelligence, driven by the digital economy, which replaces human labor with machines, thereby squeezing the rights of low-skilled workers. When the impact of the digital economy on the rights of low-skilled workers far exceeds the induced effect of the declining demographic dividend, the combined effect of the digital economy and the declining demographic dividend will further weaken the rights of low-skilled workers. However, the interaction coefficients between the digital economy effect of middle and high skilled workers and the urban demographic dividend index in columns (3), (4), (5) and (6) are not significant, which indicates that in the context of declining demographic dividend, the weakening effect of digital economy on the rights and interests of middle and high skilled workers is not obvious.

Therefore, in the context of a declining demographic dividend, the digital economy has significantly replaced the simple labor of low-skilled workers with intelligent technology, reducing their income and welfare benefits. However, the replacement of more complex, mid-to-high-skilled labor has been less noticeable. In this dual macroeconomic context of digital economic growth and a declining demographic dividend, the rights of low-skilled workers have continuously deteriorated, further highlighting the social skill gap.

Table 5. Development of Digital Economy, Decline of Demographic Dividend and Rights and Interests of Workers with Different Skill Level

	Low skills		Medium skills		High skills	
Explained variable	Realwage	Welfare	Realwage	Welfare	Realwage	Welfare
	(1)	(2)	(3)	(4)	(5)	(6)
$Digit_{rt} \times Demo_{rt}$	2.434*** (0.657)	0.994** (0.508)	1.166 (0.875)	0.757 (1.162)	–0.168 (2.057)	1.636 (2.567)
$Digit_{rt}$	–1.384** (0.566)	0.0373 (0.460)	–1.611*** (0.594)	1.147 (0.777)	0.232 (1.579)	0.862 (1.702)
$Demo_{rt}$	9.302* (5.431)	–12.104*** (2.715)	0.0738 (3.681)	–0.484 (4.945)	2.699 (8.120)	–24.646* (13.484)
Sample size	17,712	16,421	12,133	9,064	2,896	2,615
R^2	0.400	0.450	0.446	0.288	0.432	0.165

3.2.3. Heterogeneity Analysis

The research indicates that, against the backdrop of the digital economy's growth and the decline in the demographic dividend, the rights of low-skilled workers are most severely affected. To address this issue, this paper further explores the heterogeneity of the deterioration of low-skilled workers' rights from the perspectives of individual endowments, macroeconomic conditions, and government governance levels.[1] The findings reveal that, in an environment where the demographic dividend is declining, the poorer the individual endowment, the higher the level of macroeconomic development, and the worse the government governance, the more pronounced the erosion of the rights of low-skilled workers by the digital economy.

4. Conclusion and Policy Implications

This paper examines the impact of digital economic development and the decline in the demographic dividend on the rights of low- and medium-skilled workers, using data from the CHIP surveys conducted in 2002, 2007, 2008, and 2013. The study finds that: first, while the digital economy has reduced the relative income of low- and medium-skilled workers, it has improved their welfare. Second, the efficiency gains

[1] Due to space limitations, the empirical results of the heterogeneity analysis are not reported. Interested readers can contact the author for more information.

and industrial intelligence resulting from the digital economy's reorganization and reallocation of resources have weakened the relative income of low- and medium-skilled workers, but have enhanced their welfare through improved legal efficiency and government oversight. Third, the labor shortage caused by the declining demographic dividend is primarily due to the supply trap of low- and medium-skilled workers, particularly those with lower skills. Fourth, in the context of a declining demographic dividend, the digital economy has only diminished the rights of low-skilled workers. This suggests that the substitution effect of low-skilled workers driven by the digital economy far outweighs the labor shortage effect caused by the declining demographic dividend, and that the impact of individual endowments, macroeconomic conditions, and government governance levels on the rights of low-skilled workers varies significantly.

Based on the above research, this paper proposes the following policy implications: First, improve the capabilities and competencies of low- and medium-skilled workers from both individual and societal perspectives. From an individual standpoint, these workers should actively enhance their education levels, participate in various social training programs, or improve their skills through "learning by doing". From a societal perspective, the government should guide digital capital in creating employment opportunities and improve the income conditions of vulnerable workers. Second, leverage digital governance to enhance the welfare of low- and medium-skilled workers and advance the modernization of government governance. Authorities should harness the regulatory role of the digital economy and properly balance digital governance with inclusive growth. Third, accelerate the reform of the household registration system to support low-human-capital groups. The government should actively promote reforms to ensure the implementation of social security policies for low-skilled workers without urban household registration, appropriately extend compulsory education for disadvantaged groups, and further improve the coverage of compulsory education.

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