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论文题目： The Impact of Digital Capital on Gender Wages——Empirical Analysis Based on CGSS

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论文题目 The Impact of Digital Capital on Gender Wages——Empirical Analysis Based on CGSS

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论文摘要 With the advent of the digital economy, digital capital has become a key component for accumulation and growth, which will inevitably impact individual's income and psychology. This paper constructs a digital capital index from two levels, namely, digital access and digital capabilities, while using China Comprehensive Social Survey (CGSS) data to empirically analyze the impact of digital capital on wages. Studies have found that digital capital positively impacts women's wages, exceeding the impact on men's wages. Therefore, digital capital has significantly narrowed the gender wage gap. The decomposition of the contribution revealed that compared with men, the premium effect of digital capital on wages is smaller for women. Further analysis of heterogeneity shows that digital capital mainly played a role in narrowing the gender wage gap among low- and middle-income groups, which also played a greater role in the western region.

关键词 digital capital; gender wage; contribution breakdown

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1 Introduction

With the development of core technologies, the improvement of information technology systems and the gradual acceleration of the construction of digital infrastructure, the digital transformation of traditional industries and agricultural economies is becoming visible. From the "dual gigabit" network coordinated development action plan and the 5G application innovation action plan promoted by the Chinese government to increasingly mature technological developments, under the context of the fragile recovery of the global economy caused by the 2019 coronavirus pandemic, the digital economy has become a key steppingstone to sustainable development. Based on the 2021 Global Digital Economy Conference, the scale of China's digital economy in 2020 is nearly 5.4 trillion US dollars, ranking second in the world. In terms of year-on-year growth (9.6%), China ranks first in the world. The "Research Report on Employment Development in China's Digital Economy: New Forms, New Models, and New Trends (2021)" issued by the Chinese Academy of Information and Communications Technology also pointed out that employment structures and employment qualities have been profoundly affected by the digital economy. Recruitment positions in the field of digital industrialization accounted for 32.6% of the total number of recruits, accounting for 24.2% of the total number of recruits; during the same period, the scale of digital industrialization added value, which accounted for roughly 20% of the digital economy's scale. The report also highlighted that the regional gaps in the digital economy have led to the concentration of high-end jobs in eastern China, which brought a virtuous circle of talent's supply and demand simultaneously.

Differences in the digital economy exist not only among regions, but also between genders. Based on the 2019 ITU data,4.1 billion people worldwide now have Internet access, a 5.3% increase from 2018. However, the difference in Internet penetration rate among men and women has also increased from 11% in 2013 to 17% in 2019, which indicates that women in most countries are lagging behind men in using and benefiting from digital technologies. The 47th Statistical Report on China's Internet Development Status released by the CNNIC showed that as of December 2020, the number of Chinese Internet users was 989 million, and Internet penetration rate reached 70.4%, which is a5.9 percentage points inclination from March 2020. Concurrently, the number of mobile phones users in China is 986 million, among them, 99.7% of users use mobile phones for Internet access. Moreover, the ratio of male to female mobile phone users is 51.0:49.0, which is approximately the same as the male to female population ratio. Thus, with the development of the digital economy, have women's wages increased accordingly? As women's own digital capital (a detailed definition below is provided below) increases, can the gender wage gap be narrowed? Ultimately, this paper focuses on such questions.

As the digital economy era approaches, women are also empowered by gaining more access to job opportunities, especially when information and communication technology (ICT) products, and businesses gradually penetrate into various industries and fields, breaking the constraints of time and space. Currently, 80% of live webcasts are women, 70% of cloud customer services are women, and 70% of travel planners are women. In recent 20 years, Alibaba's e-commerce platform has served over 12 million sellers, of which 50% are women. In traditional workplaces, women were often disadvantaged by unbalanced development and insufficient utilization of resources, such as long-term conflicts between going to work and providing domestic childcare. The development of the digital economy has broken through the occupational gender barriers by granting women more opportunities for employment and the ability to allocate time. Concurrently, unlike many traditional industries, the digital economy does not require intense physical strength and labor, which weakens the physical advantage that men originally enjoyed due to genetic differences. Contrarily, the digital economy favors brainpower.

Zhaopin Recruitment released the "2020 China Women's Workplace Status Survey Report," which comprises 65,956 effective samples, and unveiled that the overall salary of women in the workplace is 17% lower than the overall salary of men, but the income gap is rapidly narrowing. Gender wage gaps in the labor market persist in different industries and regions, and various conclusions and opinions remain on whether the Internet positively affects gender wage gaps. On the one hand, Bustelo (2019) found that ICT and science, technology, engineering, and mathematics (STEM) skills bring significant positive returns to men and women but are clearly more beneficial to men. On the other hand, some scholars held opposite views. Viollaz (2020) used individual-level panel data that included labor market outcomes, Internet usage, and gender-biased social norms. He found that Internet usage increased the participation of female labor force but did not affect the participation of male labor force. Online job recruitment may explain some of the reasons for an increase in the participation of females, but this remains exclusive given that only aged and skilled women can access the benefit. Contrastingly, Chinese scholars have done less research on the gender wage gap in the digital economy. Among them, some of the most relevant include: how the use of the Internet can narrow the gender wage gap (Qi and Liu, 2020); research on the relationship between the Internet and undergraduates and graduate students as well as college graduates (Zhao and Zhou, 2019); how the Internet reduces the income gap between rural residents and urban residents (Cheng and Zhang, 2019); how the Internet reduces the gender wage gap among low- and middle-income groups (Mao et al., 2018).

Where does the gender wage gap come from? Studies have been conducted to explore this question. For instance, Litman (2020) pointed out that the driving factors of the gender pay gap can be divided into a few types: human capital or productivity factors (such as education, skills, and labor experience), industry or occupational separation, and gender-specific time flexibility restrictions that may affect promotion and pay. Additionally, gender discrimination exists in recruitment, promotion, assignment, and/or compensation. Using Oaxaca–Blinder analysis, Bustelo (2019) concluded that up to 80% of the hourly wage gender gap may be because women receive lower returns on STEM skills than men.

Internet usage has played an important role in increasing women's labor participation and women's wages. However, the discussion in the context of the digital economy remains limited. The digital economy is a relatively broad concept of the Internet economy. Fundamentally, it is a comprehensive concept, which mainly manifested in the integration between the new generation of information technologies, such as the Internet, big data, and artificial intelligence, and traditional industries, including the network, digital, and intelligent processes of economic forms. Therefore, under the context of the digital economy, the mechanism and size of the impact on the female labor force must be explored.

This paper intends to construct a digital capital index to describe and measure individual digital capital stock from two levels, digital access and digital capabilities, to analyze the mechanism of digital capital's impact on the gender wage gap. To use the 2017 China Comprehensive Social Survey (CGSS) data, this paper establishes an econometric model and empirically study the impact of digital capital on gender wage gaps and its main sources.

2 Digital Capital Index and the Mechanization of Influences

Digital capital is similar to human capital given that it can be understood as the deepening of human capital under the digital economy. Schultz, the founder of human capital theory, pointed out that human capital is the ability of a person to be a producer and consumer. Such capital an investment in the workers' abilities to obtain knowledge, skills, and health. Deriving from this definition, human capital has two important characteristics, the ability to be accumulated and the ability to be value added. Under the context of digitalization, the connotation of human capital is much more than what was mentioned. First, investment channels are more diversified. Human capital investments are mainly done through school education, but under the context of digitalization, the Internet and smart devices have became the main channel for investments. People can acquire knowledge and skills through different websites or applications. Second, the return of capital investment is only materialistic. Although the return of human capital is embodied in material benefits, in the context of digitalization, people not only acquire monetary income, but also obtain a sense of accomplishment in "likes." Although most of these "rewards" will eventually be converted into material rewards on the platform, anchor, bloggers, or youtubers have also obtained spiritual satisfaction under the crowd and onlookers of fans. This paper found that similar to human capital, digital capital is also accumulative and value added. Nonetheless, digital capital can reflect the new changes under the digital context better than human capital.

Digital capital differs from human capital, knowledge capital, and intangible assets. Research on the impact of Internet on individuals has undergone three stages (Rangedda et al., 2020). The first stage is Internet access. An important variable at this stage is the investment in infrastructure construction, such as the broadband Internet. However, research in this area gradually disappeared as the spread of the Internet and its influence became more prominent. The second stage is Internet usage and participation. Now is the time to consider the third stage: what people receive from the Internet. Therefore, Rangedda et al. 2020 established a digital capital index based on digital access and digital capabilities. Digital access is characterized by aspects, such as digital equipment, locations, the quality of connection, time to connect, helping others, and training access. Digital capabilities mainly refer to the ability of individuals to obtain information, create information, and solve problems in the digital economy, including information and knowledge, communication and cooperation, digital content creation, network security awareness, and problem-solving capabilities. Based on this index analysis framework, we constructed two similar indicators: second-and third-level indicators (see Table 1). The corresponding data come from the CGSS questionnaire, while the corresponding questionnaire questions and question numbers are shown in the last column of Table 1. Based on these third-level indicators, this paper uses exploratory factor analysis (EFA) to reduce dimensionality and ultimately obtain a digital capital index.

Table 1: Level indicators of the digital capital index

Second-Level Indicator	Third-Level Indicator	Number of the CGSS Questionnaire
Digital Access	Digital Infrastructure	C50 A30d A30e A30f
	Location and Quality	C51
	Time Connected	C39 C40 C66
Digital Capabilities	Information and Knowledge	C41 C43 C44 C60 A30c
	Communication and Cooperation	C42 C45 C46 C47 C48
	Digital Content Creation	C56 C57 C58 C59
	Network security	C49 C52 C53 C54 C61 C62
	Problem Solving	A30g A30h

Note: Refer to http://cgss.ruc.edu.cn for details about the CGSS Questionaire.

Intuitively, individuals with a higher stock of digital capital generally have higher wages. For men and women, digital capital stocks also differ due to the difference in gender, causing the resulting gender wages to also differ. For example, in an agrarian society, more physical labor is required, meaning that the wealth of the society is mainly created by men, which renders men's income and social status to be relatively higher. In the industrial society, especially with the development of large-scale machineries, the proportion of manual labor has declined. Women and even child labor became the labor force that capitalists are vying to hire.

Given that women were generally more attentive and patient, they accounted for a relatively high proportion of employment in the textile industry. In the age of information, the weakness of women's physical strength is even less obvious, given their advantage of being good at coordinating and communicating made them stand out among all. Specifically, the digital economy can increase women's wages in three ways, narrowing the gender wage gap with men. First, the digital economy has created more jobs suitable for women. For example, jobs, such as microbusiness and e-commerce can not only help women utilize their skills in communication and socializing, but also allow them to have spare time to attend to their families, given that such transactions can be performed at home. Second, the cost of searching for information in the digital age reduced, and it is easier for women to find matching jobs. Third, with the help of digital means, women's labor productivity can be improved, thereby increasing women's wages. (The latter two aspects may similarly impact men and women)

Below, we establish an econometric model to empirically analyze the impact of digital capital on wages, gender wages, and the impact of gender wage gaps.

3 Data, Model, and Variables Descriptions

3.1 Data source

This paper uses the 2017 CGSS data for empirical testing. The data uses stratified sampling to widely cover 31 provinces. Since 2017, the questionnaire has added a questionnaire on personal Internet use, which indicates that the latest released relevant data was 2017. After excluding samples with missing data in this paper, 2,224 valid observation samples in 2017 were obtained. In addition, the questionnaire includes questions, such as the users' use of the Internet and whether the Internet is used as an information channel. The database is often used in related research on Internet and the labor market in the existing context, and it has a degree of authority and representativeness.

3.2 Model

This paper uses the following measurement model to examine the degree of influence of digital capital stock on gender wage levels, namely:

$$lnwage_i = \alpha_i + \beta_i DCI_i + \gamma_i X_i + \varepsilon_i.$$

In the formula, the explained variable $lnwage_i$ is the logarithm of hourly wage; the core explanatory variable DCI_i is the stock of individual digital capital; X_i is the control variable, including gender, age, marital status, household registration status, education years, work experience, and family economic status. Among them, to examine whether an inverted U-shaped relationship exists between age and wages, age square/100 is also introduced. α_i, β_i, γ_i are the corresponding regression coefficients; ε_i is the error term; the subscript t is the individual unit. Using the OLS method, the overall and gender-specific samples were regressed to analyze the influence of digital capital on the average wage.

On this basis, this paper adopts the quantile regression method to examine the difference in the impact of digital capital stock on gender wage levels at different positions in the distribution of wage conditions. The point of using quantile regression is that it is not affected by extreme values, thus the person who uses quantile regression can get more robust regression results. The specific quantile regression model is:

$$Q_{i\theta}(Y_i|X_i) = X_i\beta_{i\theta} + u_{i\theta}.$$

In the formula, $QQ_{i\theta}(Y_i|X_i)$represents the conditional quantile corresponding to the quantile θ given the explanatory variable X_i. Any specific quantile can be selected for parameter estimation in quantile regression. The representative quantiles selected in this paper are 0.25, 0.50, and 0.75, and the coefficient estimates are obtained by minimizing the following equation:

$$\min \sum_{i:Y_i \geq X_i\beta(\theta)} \theta|Y_i - X_i\beta(\theta)| + \sum_{i:Y_i \leq X_i\beta(\theta)} (1-\theta)|Y_i - X_i\beta(\theta)|$$

3.3 Variable Description

The explained variable in this paper is the hourly wage rate (see Table 2), using personal annual income/ (52 weeks x weekly working hours) to calculate the hourly wage, then take the logarithmic value. Given that time difference is an important reason for gender wage difference to exclude working time factors, this paper uses hourly wage rate as the explained variable for analysis. This paper also introduces control variables: gender, age, age squared/100, marital status, household registration status, education level, work experience, and the family's economic status. Among them, the family's economic status is introduced through dummy variables. Taking the far lower than average level as the benchmark group, four dummy variables are introduced below, namely, the average level, the average level, above the average level, and much higher than the average level. The descriptive statistical results of the above variables are shown in Table 2.

Table 2: Statistical description of the main variables

Variables	Variables' Description	Sample Size	Mean	Standard Deviation	Minimum	Maximum
DCI	By the EFA Method	1,227	-12.95	34.74	-147.24	70.33
ln wage	Ln (personal annual income/(52×week working hours))	1227	10.46	1.20	3.65	15.34
Gender	Male=0，Female=1	1227	0.42	0.49		
Age	Calculated the actual age according to the survey year	1227	40.48	10.62	19	82
$Age^2/100$	Square of Age/100	1227	17.51	8.95	3.61	67.24
Marriage	Unmarried/Divorced=0，Married/Live together=1	1227	0.81	0.39	0	1

Education	Primary School and below=6，Junior High School=9，Ordinary high school / vocational high school / technical school / technical secondary school=12，Junior College=15，Undergraduate=16，Postgraduate and above=19	1227	15.61	0.722	15	19
Experience	Years of experience in non-agricultural work	1227	14.31	13.40	0	20
Fe.status	Far below average level=1 Below average level=2 Average level=3 Above the average level=4 Much higher than the average level=5	1227	2.69	0.71	1	5
Region	Divided into three areas according to the survey: eastern, central, and western	1227	-	-	-	-
Interplus	Internet + Digital Economy Index (Tencent Research Institute)	1227	13.19	13.17	0.92	58.52

4 Empirical Analysis

4.1 Average impact of digital capital stock on gender wages

This study performed OLS regression on the overall, male, and female wages in 2017 to examine the difference in the impacts of digital capital stock on gender wages. The specific regression results are shown in Table 3.

The regression results show that the impact of digital capital on overall wages is significantly positive at the 1% level, and its impact coefficient is 0.005, indicating that digital capital has a significant wage premium effect. In terms of gender, the positive effect of digital capital on women's wages is higher than that of men, indicating that digital capital is more conducive to raising women's wages.

The correlation between age and its square term and the wage level of workers is positive, but not significant. Being married positively impacts males' wages, but negatively impacts females' wages although insignificant. This may be related to the fact that men have a stronger sense of responsibility to financially support the family after marriage, while women face pressure to give birth and take care of the family after marriage, thus might temporarily launch the labor market. Within the sample range, the overall education return rate is roughly 16%. Compared with men, the education return rate of women is significantly higher. However, compared with men, the return on women's income from work experience is lower. Regarding the family's economic status, relative to the benchmark group of being far below average, below average, average, above average, and far above average all positively impact overall wages and are above average. As the family's economic status improves, the premium effect on wages will gradually increase significantly. Thus, a positive relationship exists between family economic status and wage levels. Regarding regional characteristics, the average wage level in the eastern region is significantly higher than that in the central and western regions.

Table 3: OLS regression results of the impact of digital capital stock on gender wages

Variable	Full Samples	Male	Female
DCI	0.005^{***}	0.004^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)
age	0.041^{*}	0.019	0.061
	(0.021)	(0.025)	(0.041)
$age^2/100$	-0.077^{***}	-0.064^{**}	-0.089^{*}
	(0.024)	(0.028)	(0.050)
gender	-0.463^{***}	-	-
	(0.060)	-	-
marriage	0.102	0.293^{***}	-0.113
	(0.088)	(0.110)	(0.148)
education	0.158^{***}	0.103^{*}	0.222^{***}
	(0.041)	(0.053)	(0.065)
experience	0.019^{***}	0.025^{***}	0.012^{***}
	(0.003)	(0.003)	(0.004)
below-average	0.152	0.223	0.000
	(0.145)	(0.165)	(0.280)
average	0.433^{***}	0.554^{***}	0.222
	(0.141)	(0.160)	(0.274)
Above average	1.015^{***}	1.063^{***}	0.856^{***}
	(0.168)	(0.200)	(0.305)
well above average	2.146^{***}	1.930^{***}	3.050^{***}

	(0.531)	(0.582)	(1.126)
West	-0.702***	-0.569***	-0.867***
	(0.079)	(0.098)	(0.130)
Midland	-0.486***	-0.396***	-0.619***
	(0.071)	(0.090)	(0.114)
Constant	7.362***	8.492***	5.787***
	(0.767)	(0.945)	(1.329)
Observations	1,227	714	513
R^2	0.279	0.287	0.261
Adjusted R^2	0.272	0.275	0.243
F Statistic	36.156***	23.563***	14.733***

Note: The standard errors are in parentheses, and the superscripts ***, **, * indicate significances at the statistical levels of 1%, 5%, and 10%, respectively. This similarly applies to the following table.

4. 2 Influence of digital capital stock on gender wage quantile

To explore the differences in the impact of digital capital on gender wages at different quantiles of wage distribution, this paper further uses quantile regression to analyze gender wages of various groups in 2017. The specific regression results are shown in Table 4.

Table 4: Quantile regression results of the impact of digital capital stock on gender wages

Variable	Male		
Quantile	0.25	0.5	0.75
DCI	0.00269** (0.00119)	0.00211 (0.00143)	0.00513*** (0.00139)
Control Variable	Yes	Yes	Yes
Sample Size	714	714	714
Variable	Female		
Quantile	0.25	0.5	0.75
DCI	0.00394*** (0.00138)	0.00411*** (0.00092)	0.00453*** (0.00148)
Control Variable	Yes	Yes	Yes
Sample Size	513	513	513

The regression results reveal that as the value of quantile rises, the influence of digital capital stock on the gender wages of men and women in the sample range is also on the rise. Compared with women, digital capital impacts men's wages at the 25th and 50th quintiles. However, the premium has a smaller impact, and at the 75th percentile, the impact of digital capital on men's wage premium is higher than that on women. Digital capital has played a greater role in low- and middle-income women. For high-income groups, it has a greater impact on men. This may be related to the fact that men are more interested in the emerging Internet, meanwhile the proficient use of the Internet can help improve men's relative employment competitiveness. Especially, compared with low-income groups, the digital capital stock of high-income groups is relatively high. Thus, the use of the Internet by high-income groups is more inclined to use office tools, such as instant messaging and mail transmission, whereas Internet entertainment is less involved. Concurrently, because men are more interested in the entertainment use of the Internet, among men's low- and middle-income groups, the stock of digital capital will be less than that of women’s high-income groups. Given the vigorous development of digital industrialization and the increasing popularity of media, such as computers and mobile phones, more and more women started to come into contact with the Internet and new media, especially the use of digital technologies, such as e-commerce operations, information search, Internet celebrity live broadcasts, and social platforms, which have significantly magnified the numbers. Alongside with the empirical result, the premium effect of capital on wages is more obvious for low- and middle-income earners.

Among other control variables, with the increase in the number of quantiles, the positive impact of years of education on male wages in the 2017 sample range showed a downward trend. For the same effect on women’s wages, the longer they have been educated, the lower their wage premium effect. This may be because of the widespread usage of the Internet and the diversification of income sources. Compared with low-income groups, female high-income groups have a relatively lower rate of return to education. Regarding work experience, as the number of quantile points increases, the positive influence of work experience on men in the sample interval also shows a gradual upward trend, whereas the positive influence of work experience on women’s wages shows a U-shaped trend. Regarding regional characteristics, compared with the eastern region, with the increase in the number of quantiles, the influence of the central and western regions on the wage level shows a decreasing trend, indicating that the state’s precision poverty alleviation in the central and western regions has increased, and the income gap between regions has a gradually narrowing trend.

4.3 Oaxaca-Blinder decomposition results

The previous analysis uncovered that digital capital impacts gender wage gap. To further the source of this impact, we decomposed the contribution degree. In this paper, the Oaxaca–Blinder decomposition method is used to decompose the gender wage gap in the sample of each year and the contribution of various influencing factors, including digital capital stock, to the total gender wage gap can be decomposed into feature differences and coefficient differences. The specific decomposition results are shown in Table 5.

Table 5: Oaxaca–Blinder Decomposition Results of Gender Wage Differences

Decomposition Term	Variable	Coefficient Value	Percentage(%)
	Total Wage Gap	0.3974	100
Characteristic Effect	DCI	−0.0204	−5.13
	Age	−0.0250	−6.28
	Marriage	0.0005	0.01
	Education	−0.0036	−0.91
	Experience	0.0288	7.25
	Fe-status	−0.0181	−4.54
	Region	0.0071	1.79
	Total Count	−0.0311	−7.81
	DCI	−0.0166	−3.88
	Age	−1.0071	−235.02
Coefficient Effect	Marriage	0.3028	70.67
	Education	−1.6831	−392.78
	Experience	0.1799	41.98
	Fe-status	2.5331	591.16
	Region	0.1195	27.88
	Total Count	0.4285	107.81

From the results of the decomposition, compared with the difference in characteristics, the coefficient difference accounts for a significantly higher proportion of the total gender wage difference. The unexplainable part of the total wage difference caused by market discrimination is quite high. The possible reason is that women are facing serious gender discrimination. Concurrently, due to traditional social norms, family roles, and physical differences, women in the labor market often face an unequal employment environment and employment opportunities of "equal work but different pay," resulting in obvious gender wage differences between men and women.

In terms of characteristic difference, the characteristic difference of digital capital is negative, accounting for −5.13% of the total difference, whereas for the coefficient effect part, the coefficient of digital capital stock is negative, accounting for −3.88% of the total difference. These results indicate that for women, relatively speaking, the premium effect of digital capital stock on wages is even smaller.

Given that the variable years of education, the characteristic difference, coefficient difference, and corresponding ratio are all negative, as well as the fact that the coefficient difference is relatively high, these all indicate that the individual endowment characteristics of education years and the difference in education return rate have significantly reduced the gender wage gap. This may be related to the higher education level of women overall. In terms of other decomposition terms and characteristic differences, in each year, the characteristic differences and corresponding proportions of marital status, working years, and regional characteristics are all positive, signifying that the differences in individual endowment characteristics, such as marital status, working years, and region have further widened the gender wage gap. The characteristic difference values and corresponding proportions of individual age and family economic status within the sample range are positive, which further indicates that the differences in individual age and family status have significantly reduced the gender wage gap. In terms of coefficient differences, the coefficient differences and corresponding ratios of age and years of education within the sample range are negative, whereas the coefficient differences and corresponding ratios of marital status, work experience, family status, and region are positive, indicating that in the labor market, the difference in age and years of education faced by men and women has significantly reduced the total gender wage gap, whereas the difference in the rate of return of factors, such as marriage and work experience has significantly increased the gender wage gap.

4.4 Quantile decomposition results

Based on quantile regression analysis, the quantile decomposition method can be further used to decompose the source of wage differences. When performing quantile decomposition, focus on the 0.25, 0.5, and 0.75 representative wage quantiles, as well as the difference in characteristics and coefficients of the digital capital stock for gender wage differences at different wage quantiles. Concurrently, the work experience and the number of years of education control variables, such as, marital status, and so on are merged into "others." The specific sample quantile decomposition results are shown in Table 6.

Table 6: Quantile decomposition results of gender wage differences in the sample

Decomposition Terms	Variables	0.25	0.5	0.75
		Difference value (%)	Difference Value (%)	Difference Value (%)
Characteristic Differences	DCI	−0.0541 (−14.52)	−0.0500 (−14.32)	−0.0641 (−17.64)
	Others	0.0281 (7.54)	−0.0181 (−5.18)	0.0190 (5.23)
	Total Count	−0.0260 (−9.98)	−0.0681 (−19.50)	−0.0451 (−12.41)
Coefficient Differences	DCI	−0.0199 (−5.34)	−0.0102 (−2.92)	−0.0305 (−8.39)
	Others	0.4186 (112.32)	0.4275 (122.42)	0.4390 (120.80)
	Total Count	0.3987 (106.98)	0.4173 (119.50)	0.4085 (112.41)
Total Differences		0.3727 (100)	0.3492 (100)	0.3634 (100)

The decomposition results reveal that as the number of quantile points increases, the total gender wage differential value presents a U-shaped change trend. The absolute value of the gender wage differential reaches the lowest value at the 0.5 quantile point, whereas it is 0.25 for low-income earners and 0.75 for high-income earners. The total gender wage gap is more obvious. With the increase in the number of quantiles, the total difference of coefficients is all negative, and their proportions to the total difference are all over 100% and display an inverted U-shaped change trend of first rising and then falling, indicating an unexplainable market at the 0.5 quantile. Discrimination accounted for the largest proportion of total differences, and gender discrimination in the labor market was the main reason for wage differences. At each quantile, the total difference in characteristics is positive, and the absolute value reaches the maximum at 0.5 quantile, indicating that the difference in individual characteristics of total endowment increases the total gender wage difference, especially for the middle-income class, the effect is more obvious.

The decomposition of the core variable digital capital (DCI) shows that along with the increase in the number of quantile points, the characteristic difference value and the proportion of the digital capital stock also have a trend of first decreasing and then increasing, with its absolute value reaching the minimum at the 0.50 quantile. It shows that among the middle-income class, the stock of female digital capital is relatively low, and the characteristic difference in digital ability can significantly reduce the gender wage gap between low-income groups and high-income groups. With the increase of the number of quantile points, the proportion of the characteristic difference of the digital capital stock to the total difference is negative, and the absolute value gradually rises. This shows that for high-income groups, digital capabilities and exposure to new things on the Internet can reduce the difference between the genders to a greater extent. In the coefficient difference part, the coefficient difference of the digital capital stock is all negative, and the absolute proportion of the total difference also shows a trend of first decline and then rise. This may be because with the rapid development of the digital industry, the society is paying increasing attention to digital skills, and the salary premium for the use of digital capital by middle- and high-level-income earners is more obvious. Ultimately, the difference in the rate of return on digital capital has gradually narrowed the gender wage gap.

5 Further Discussion

5.1 Gender wage differences in digital capital of different regions

Considering that apparent differences exist in the frequency and the purpose of using the Internet among groups in different regions, it will also affect gender wage differences distinctly. Based on the questionnaire settings, this paper divides the individuals in the sample into eastern, western, and central regions according to age groups. This paper used the OLS regression method to further investigate the impact of the digital capital stock of different regions on gender wage changes. The specific regression results are shown in Table 7.

Table 7: OLS regression results of digital capital stock on gender wages in different regions

Variable/ Group	Eastern Region			Central Region			Western Region		
	Total	Male	Female	Total	Male	Female	Total	Male	Female
DCI	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.002)	0.003 (0.002)	0 (0.003)	0.006* (0.003)	0.002 (0.002)	0 (0.003)	0.003 (0.003)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.224	0.278	0.170	0.189	0.163	0.237	0.259	0.252	0.299
N	653	384	269	327	185	142	247	145	102

The regression results reveal that, holistically, the positive impact of digital capital on groups in the eastern region is the most significant. Although the stock of digital capital in the central and western regions positively impacts wages, it is not outstanding. Compared with the central and western regions, the eastern region has a higher economic level and a higher Internet penetration rate. Moreover, the level of individuals' acceptance of new Internet things and applications is higher in the eastern region than that of the central and western regions. Meanwhile, because the eastern region is mostly plain, the coverage of optical fiber and 5G base stations is high, and the logistics level is developed. New digital employment models, such as computer IT industry, digital Internet-of-things, e-commerce online sales, e-sports, and webcast have effectively increased income level.

In terms of gender comparison, no difference exists in the positive effects of women's and men's wages among groups in the eastern region. The possible reason is that the overall digital capital stock level of the eastern region groups is relatively high, which reduces the wage gap between men and women caused by gender discrimination in the market. In the central and western regions, although the coefficient is not significant, it also shows that the premium effect of digital capital stock on women's wages in the central and western regions is higher. The portability of the Internet derives online working models, such as e-commerce and platform employment, which can meet women's needs in the central and western regions for ample leisure and work flexibility, providing the possibility of balancing family and work. Additionally, online entrepreneurships effectively reduced transaction operations costs, expanded market share, and obtain benefits, thereby increased the probability of women choosing to start their own businesses online, which in turn positively impacts their wages.

5.2 Oaxaca-Blinder decomposition results of different regional groups

Based on the previous analysis and the estimation of the influence of the digital capital stock of different regional groups on the mean value of gender wages, to further investigate the degree of gender wage discrimination faced by groups in the eastern, central, and western regions, influencing factors, and possible changing trends, this paper presents the decomposition results of gender wage differences in the Oaxaca–Blinder. Concurrently, to focus on the analysis of the digital capital stock variables, the control variables, such as age, marital status, and annual education salary are combined into "others." The specific decomposition results are shown in Table 8.

The decomposition results reveal that from the perspective of total differences, the total differences among groups in the western region are the largest, followed by the central regions. From the perspective of differences in general characteristics, the differences in gender wages entailed by individual endowments in the central region are more noticeable, which has narrowed the wage gaps of different genders to a greater extent. In the eastern and western regions, the gender wage differences caused by the differences in total characteristics are all positive. The characteristic differences in the eastern region are also smaller than those in the western regions, indicating the contribution of the total gender wage differences caused by the differences in endowment characteristics relative to the western region is relatively small, further proving that differences in personal endowments in the eastern region have a relatively low impact on gender wages.

Table 8: Oaxaca–Blinder decomposition results of gender wage differences in various regions

<table>
<tr><th colspan="3">Groups/Decomposition Terms</th><th>Coefficient Value</th><th>Percentage (%)</th></tr>
<tr><td rowspan="7">Eastern Region</td><td rowspan="3">Characteristic Differences</td><td>DCI</td><td>−0.0086</td><td>−2.75</td></tr>
<tr><td>Others</td><td>0.0179</td><td>5.75</td></tr>
<tr><td>Total Count</td><td>0.0093</td><td>3.00</td></tr>
<tr><td rowspan="3">Coefficient Differences</td><td>DCI</td><td>−0.0094</td><td>−3.01</td></tr>
<tr><td>Others</td><td>0.3112</td><td>100.01</td></tr>
<tr><td>Total Count</td><td>0.3018</td><td>97.00</td></tr>
<tr><td colspan="2">Total Differences</td><td>0.3112</td><td>100</td></tr>
<tr><td rowspan="7">Central Region</td><td rowspan="3">Characteristic Differences</td><td>DCI</td><td>−0.0422</td><td>−9.18</td></tr>
<tr><td>Others</td><td>−0.1152</td><td>−25.02</td></tr>
<tr><td>Total Count</td><td>−0.1574</td><td>−34.20</td></tr>
<tr><td rowspan="3">Coefficient Differences</td><td>DCI</td><td>−0.0374</td><td>−8.12</td></tr>
<tr><td>Others</td><td>0.6553</td><td>142.32</td></tr>
<tr><td>Total Count</td><td>0.6179</td><td>134.20</td></tr>
<tr><td colspan="2">Total Differences</td><td>0.4604</td><td>100</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">Characteristic Differences</td><td>DCI</td><td>−0.0201</td><td>−3.97</td></tr>
<tr><td>Others</td><td>0.0997</td><td>19.68</td></tr>
</table>

Western Region		Total Count	0.0796	15.71
	Coefficient Differences	DCI	−0.0200	−3.95
		Others	0.4469	88.25
		Total Count	0.4269	84.29
	Total Differences		0.5064	100

From the perspective of the total coefficient difference, the total coefficient difference in the central region accounts for the highest proportion of the total difference, followed by the western region. In the central region, the degree of gender discrimination in the labor market is relatively high. This may be because the financial and service industries in the central region are relatively lower than the eastern region, and the fixed population ratio is also higher than that in the western region.

For the use of decomposition items for digital capital stock, in terms of characteristic differences, the characteristic difference value and the proportion of the total difference in the digital capital stock of each regional group are all negative values. In terms of absolute value, the characteristic difference value of the digital capital stock of the central region and the proportion of the total difference are relatively high. This may be because traditional industries have been greatly impacted by the Internet, and the migration of transportation and tertiary industries to the central and western regions has led to the development of the Internet in the central region. With the rise of short video platforms, such as Tiktok (Douyin) and Kuaishou, the central region's denser population compared with the western region will also bring a greater wage premium effect. Regarding the coefficient system difference, it also shows that among groups in the central region, the degree of reduction in the gender wage gap caused by the digital capital stock is higher than that in the eastern and western regions. The labor market in traditional industries has been affected by intensifying Internet penetration, and the central region has suffered a greater impact.

6 Conclusion and Implications

This paper discusses the mechanism by which digital capital affects women's wages in the context of the digital economy. The main path of influence is to increase women's labor participation, job matching, and labor productivity. On this basis, a digital capital index was constructed from the two levels of digital capital and digital capabilities, and the 2017 CGSS data were used to examine the total impact of digital capital on gender wages and the difference in income distribution at different quantiles.

Additionally, this paper analyzes impacts of the decomposition of wage differences and explored the heterogeneous impact of digital capital of various regions on changes in gender wage differences. The study found that: (1) Digital capital has a significant positive impact on the overall wage level, with a greater impact coefficient on women, indicating that the gender wage gap can be narrowed; from the decomposition results, the total wage gap caused by market discrimination is unexplainable, though some of the high proportions may be due to women facing more gender discrimination. (2) With the increase of quantile points, the impact of digital capital on wages has generally shown an upward trend, but there remain gender differences. For men, the highest impact is the high-income group, whereas the impact on the middle-low-income group being comparatively small, or sometimes even insignificant; for women, the impact of digital capital on low- and middle-income groups is highly significant. (3) The gender wage decomposition of digital capital shows that gender discrimination in the labor market is the main cause of wage differences. For middle-income groups, differences in the characteristics of individual total endowments are the main reason for the increasing gender wage gap. (4) From a regional perspective, group digital capital in the western region has the greatest impact on the total gender wage gap, followed by the central region. The differences in gender wage characteristics entailed by individual endowments in the central region are more significant. Based on the above empirical analysis conclusions and the context of the current rapid development of the digital economy, to further increase the stock of individual digital capital and give full play to its role in narrowing the gender wage gap, there exist few policy implications that can be done.

The first is to continue to increase investment in digital infrastructure construction and attach importance to the improvement of digital capabilities and soft power simultaneously, thereby increasing the stock of individual digital capital. Invest more in digital technologies, such as 5G, cloud computing, blockchain, and so on, so that individuals can enjoy more dividends in digital infrastructure. However, with the popularization of broadband Internet and intelligent terminal equipment, the differences between individuals in digital access will be eventually wiped out. Therefore, the public sector must further improve the investment of individuals in digital capabilities, such as education for women in Internet usage or provide free online learning opportunities to improve the individual's participation in digital economic activities and the ability to absorb and process information, so that individuals are not only passive receivers of knowledge, but also creators of knowledge.

The second is to provide corresponding digital skills training for women, especially low- and middle-income women. The decomposition of the sources of wage differentials in digital capital reminds us that digital capital has a greater impact on the reduction of the wage gap between low- and middle-income groups. Therefore, the society must pay more attention to digital capital investment in low- and middle-income women. We can also push for education content services in a targeted manner or provide study vouchers and tax relief. Concurrently, the elimination of gender discrimination should also receive attention in the context of the digital economy. The third is to strengthen the investment in the construction of digital access and the training of digital capabilities in the western region. The above research shows that digital capital in the western region is the main source of the gender wage gap. Therefore, the construction of digital infrastructure in the western region must be increased, the training of individual digital capabilities in the western region must be strengthened, and exchanges and interactions with other regions must be made.

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论文选题的来源于在日常生活中注意到越来越多的人参与线上经济，比如网红直播带货等，因此想到数字经济对于收入的印象。由于女性权利一直是一个非常重要并且热门的社会问题，由此延伸到对于数字经济对性别收入差异的影响。本篇论文仅一位学生完成，因此无具体分工。指导老师为无偿指导，起到的作用为在专业学术问题方面答疑解惑，指导学生。