

# Which employment mode is more competitive in a digital economy? A study on income differences of flexible employment

*Kangyin Lu, Liwen Jia, Si Chen*

## Abstract

The digital economy has increased the competitiveness of economies worldwide, accelerated dramatic changes in employment trends, and driven the rapid growth of flexible employment in China. We use micro survey data from the China General Social Survey (CGSS) in 2013, 2015, 2017, and 2018 to empirically analyze the income competitiveness differences under different flexible employment modes in the context of the digital economy as well as the differences in income competitiveness between genders, and deconstruct the differences. It is found that the development of digital economy improves income competitiveness in the flexible employment market. The income competitiveness of the digital flexibly employed is higher than that of the traditionally flexibly employed. And in terms of gender differences, females benefit more from digital flexible employment modes. Moreover, the self-employed have higher income competitiveness than the regularly employed, especially the digital flexible self-employed. Finally, in the context of the rapid development of the digital economy, there is a two-tier structure in the flexible employment labor market, and the wage penalty suffered by flexible workers at the bottom of the wage distribution is greater, which increases the internal income gap of flexible workers and exacerbates the income polarization. Therefore, public policies should focus on enhancing the employment competitiveness of flexible employment workers in the low-income quantile.

**Keywords:** digital economy, digital flexible employment, flexible employment, income competitiveness, gender differences

**JEL Classification:** J21, J31, D31

## 1. INTRODUCTION

The emergence of business ecosystems, and a platform economy based on “Internet +,” 5G, intelligence, and big data, has reshaped the labor market, leading to new trends in employment. The form of employment has transformed from “traditional” to “gig-based,” with transitions from traditional employment to digital employment, and from professional employment to compound employment. The International Labor Organization (ILO) has released a report stating that there are currently two billion workers in flexible employment worldwide in 2022, accounting for more than 61% of the total global workforce (Samaan et al., 2023). According to a 2016 McKinsey Global Institute report, in Spain and Greece, where unemployment rates are high, self-employed flexible employment has become a fairly common form of employment. In the United States, from 2005 to 2015, the proportion of flexible workers in the total labor force increased from 10.7% to 15.8% (Katz & Krueger, 2018). According to a 2018 Gallup poll, flexible workers in the U.S. comprise 36% of the total workforce (Mcfeely & Pendell, 2018). A 2019 report by the Bank of Canada noted that flexible employment accounts for one-third of the total workforce, with trends more pronounced among part-timers, youth groups, and provinces with higher unemployment rates (Kostyshyna & Luu, 2019). According to a report by the Japanese job-seeking company Lancers Inc., 7.44 million Japanese held at least two jobs in 2018, accounting for about 11% of the total workforce, which was higher than the 5.33 million

witnessed in 2015 (Zheng, 2018).

In China, which has witnessed the transition from a planned economy to a socialist market economy, employment mode has also undergone profound changes, from the “lifetime employment system” to the “contract system,” and then to the “flexible system.” Notably, workers’ autonomy in flexible employment has continuously improved over the years (Qian et al., 2022). Li and Gao (2023) found that the China’s urban informal employment has grown rapidly. The scale of flexible employment grew from 0.16% in 1978 to 62.28% in 2019. According to data from the Ministry of Human Resources and Social Security in 2020, the number of flexible-employment workers in China reached approximately 200 million. And the scale of platform employment and digital flexible employment is growing rapidly. Platforms such as the Didi (the largest online ride-hailing service provider in the Chinese market) and the Meituan (a representative O2O e-commerce platform in China) provided employment opportunities for a large number of groups with relatively low education and skills, or who were briefly unemployed due to the COVID-19 pandemic, making an important contribution to absorbing special groups into employment and greatly enhancing the efficiency of labor factor allocation and income competitiveness (Feng & Geng, 2022).

Flexible employment is an effective supplement to formal employment and plays a crucial role in increasing income competitiveness. So, what are the modes of flexible employment in China in the context of the digital economy, and how is income competitiveness? How do the differences in income competitiveness of different flexible employment modes affect employment decisions and do they cause a polarization of the flexible employment labor market? Answering these questions will help to develop a structural understanding of the rapidly developing flexible employment market and help predict the future development trend of the digital flexible employment market. So, the main contribution of this study is to supplement the relevant literature on this topic. It helps to grasp the changes in the development of China's labor market and guides the management of the digital flexible employment market to improve income competitiveness. Meanwhile, this study deconstructs the income competitiveness of different quantiles to provide a theoretical basis for enriching employment theory and exploring the development of atypical employment relationships, and has some theoretical reference value for promoting the structural transformation of the labor market in countries with economies in transition. The remainder of this paper is organized as follows: Section 2 describes the theoretical background, Section 3 presents the variables, methodology, and data, Section 4 provides and discusses the empirical results, while Section 5 is the conclusion with limitations.

## 2. THEORETICAL BACKGROUND

Flexible employment has attracted considerable attention in recent academic debates. “Flexible employment” is also called “informal employment,” and it comes from the definition of the “informal sector” provided by the economic anthropologist Keith Hart (1973). He defined the informal sector as the activity of an economic unit between the modern urban sector and the traditional agricultural sector, mainly absorbing urban unskilled workers, the unemployed, and rural migrant labor. At this stage, advances in information and communication technologies (ICT) have made it possible to develop online platforms that have dramatically changed the e-commerce landscape and brought about significant changes in the organization of work (Fahmy, 2020), and increased income competitiveness and the probability of employment, especially for female and older workers who tend to choose flexible work (Atasoy et al., 2021). ICTs are imperative for connecting people and communities, increasing innovation and productivity, strengthening economic competitiveness, and reducing poverty worldwide (Arshed et al., 2022; Stankovic et al.,

2021). It also increases labor productivity both in the short and in the long run (Acemoglu & Restrepo, 2019). Meanwhile, the new global specialization of labor across the value chain and the new business model of the network platform have had a great impact on the structure of the labor market, especially for the flexible job market (Valenduc, 2019).

A digital economy is an economic form that uses data and digital technology as production factors (Miao, 2021). This new form of work is reflected by the comprehensive utilization of online platforms, geolocation, and mobile applications on smartphones to match employer requirements and employee availability (Farrell & Greig, 2016), and is called “work-on-demand via apps” (Stefano, 2015) or “platform-based on-call work” (Valenduc & Vendramin, 2016). Cutolo and Kenney (2021) found that under flexible employment ecology, some workers have become “platform-dependent entrepreneurs.” It involves job matching, promotes work efficiency, and creates many new jobs and digital flexible employment modes (Stanford, 2017; Zervas et al., 2017). The digital economy has a positive employment multiplier (Lee & Clarke, 2019) that can improve labor literacy and income competitiveness through the digital application of education and employment skills training programs (Spante et al., 2018; Weninger, 2017). Therefore, building an effective digital economy infrastructure is currently a basic condition for improving the international competitiveness of middle-income countries (Balcerzak & Pietrzak, 2017).

Flexible employment has high work flexibility (Shibata, 2022; Hall & Krueger, 2017) and can relax time-resource constraints (Agrawal et al., 2018), creating employment opportunities (Rubery et al., 2016), and employment choices are subjective (He et al., 2019). Giovanis (2018) found that flexible employment can balance family and work. Moreover, the digital economy based on the Internet has reduced market friction (Każmierczyk & Chinalska, 2018) and lowered the information search cost of flexible workers (Chen, 2020), which has reduced females’ attachment to the labor market and further increased their chances of obtaining jobs (Zhang et al., 2023). The widespread application of the digital economy has a positive impact on economic growth and job creation (Manyika et al., 2016). Peru has one of the highest rates of flexible employment in Latin America, at 73% (Michael et al., 2022). Inga and Mark (2019) found that the proportion of flexible employment in Australia in 2017 was 55.6%. Through the RAND American Life Panel, Katz and Krueger (2018) found that 0.5% of people provide services on online intermediaries, such as Uber or Task Rabbit. After considering the impact of business cycles, Katz and Krueger (2019) found that the incidence of flexible work increased 1-2 percentage points in 2017 compared to 2000, and the growth of employment in the platform economy was an important reason for the increase in the scale of flexible employment. Other scholars have determined that, on average, informal workers earn less than formal workers, both in terms of monthly earnings and hourly wages, and the wage penalty for informal employment is substantially higher for individuals at the bottom of the wage distribution. The net hourly earnings of males in formal employment are 26% higher than those of males in informal employment and 14% higher for females in formal employment than for females in informal employment (Williams & Gashi, 2022). However, Berger et al. (2019) found that although the drivers of a U.K. car-hailing platform have lower incomes, they have higher life satisfaction, which is largely due to work flexibility.

Due to many differences in economic development, institutional environments, and social and cultural backgrounds, the growth of flexible employment differs greatly between China and developed Western countries. This study explores the income competitiveness of Chinese urban residents under different flexible employment modes in the context of the digital economy, and provides empirical evidence for international studies through a comprehensive understanding and accurate grasp of flexible employment modes and differences in China.

### 3. RESEARCH OBJECTIVE, METHODOLOGY, AND DATA

#### 3.1 Research aim

Although the current wave of the Fourth Industrial Revolution and the transition in the nature of global work is signified by macro-environmental changes and new employment trends, the situation and opportunities faced by China's labor market and workers' flexible employment are not exactly the same as those in Western countries. Hence, this study aims to gain a deeper understanding of the employment status of flexibly employed workers in China's digital employment modes, to determine the income competitiveness in flexible employment modes, and to test whether there is a two-tier structure in China's flexible labor market. We explore the factors that can help further increase the income competitiveness level of flexibly employed workers and provide targeted social security work for flexibly employed workers. Another objective is to provide a reference for the profound understanding of flexible employment under digital employment modes.

#### 3.2 Methodology

Owing to labor search costs, the labor supply curve faced by enterprises has a sloping shape to the upper right. With an increase in labor search costs, the resulting buyer's exclusive monopoly becomes more obvious. Fig. 1 depicts the job search costs of flexible employees. Assume that there are two groups of laborers with the same productivity in the labor market, that is, their marginal revenue product of labor  $MRP_L$  is equal to the  $MRP_L^*$  in the figure; between them, the job search cost of the traditional flexible employment group with a low information level is higher than the digital flexible employment group with a high information level. Fig. 1 (a) outlines the labor supply curve of the digital flexible employment groups with relatively low job search costs and the marginal revenue product curve of labor. Owing to its lower job search costs, the labor supply curve  $S_{DFe}$  is relatively flat, which means that the labor marginal expense curve  $MEL_{DFe}$  is also relatively flat. Employers seeking to maximize profits will hire the number of workers from this group of workers equal to  $E_{DFe}$  and will pay them a wage rate equivalent to  $W_{DFe}$ , which is only slightly lower than  $MRP_L^*$ .

Fig. 1(b) describes the labor supply curve and labor marginal revenue product curve of the traditional flexible employment group with low levels of information. We assume that these employees have the same labor marginal revenue products as the employees in Fig. 1(a). However, because their job search costs are higher, the slopes of their labor supply curve  $S_{TFe}$  and labor marginal expense curve  $MEL_{TFe}$  are relatively large. At the same time, the gap between their labor marginal revenue product and the wage rate is even greater. The number of employees the employer hires from this group will be equal to  $E_{TFe}$ , and the wage rate they receive will be  $W_{TFe}$ . Comparing Figs 1(a) and 1(b), although the two groups have the same productivity, the wage level of traditional flexible employees is lower than that of digital flexible employees ( $W_{TFe} < W_{DFe}$ ), and income competitiveness is even lower.

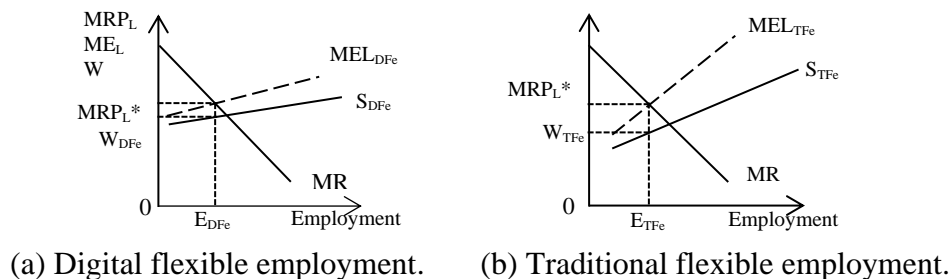


Fig. 1 – Search costs for flexible employment groups.

The direct impact of the digital economy on the labor market is the reduction of the cost of job hunting, allowing labor supply and demand to overcome the obstacles of information

asymmetry and achieve the most efficient connection. In the context of the digital economy and its externalities, the job search costs for flexible employees are further reduced, increasing employment opportunities and income competitiveness, especially for females (James, 2022), and reducing friction unemployment and structural unemployment. Thus, the following hypotheses are proposed in this study.

H1: Digital flexible workers have higher income competitiveness than traditional ones.

H2: There is a gender difference in income competitiveness among flexible workers in the context of the digital economy.

H3: The existence of a two-tier structure in the flexible-employment labor market increases the internal income disparity of flexible workers and exacerbates income inequality.

To examine the income differences of different flexible employment modes in the context of the digital economy, this study builds a benchmark regression model based on the Mincer income equation. Mincer (1974) argues that income shows a concave trajectory with age over the worker's life cycle, and then Mincer extends the income equation from age to work experience, arguing that human capital investment in work is largely guided by market demand rather than age, and that the experience learned through training and practice, i.e., learning by doing, has an important impact on earnings. Mincer uses age minus years of schooling minus time to start education as a statistical indicator to calculate work experience. He also pointed out that variables in the household environment, health investments, macroeconomic, and other control variables also need to be included in the income equation, so, this study extends Mincer's model to include individual, family, and macroeconomic factors. The regression model is shown in Equation (1), and variables are defined as shown in Table 1.

$$Lnincome = \alpha + \beta X + \sum \gamma_i Z_i + \delta Year_i + C_i + \varepsilon_i \quad (1)$$

The dependent variable is the logarithm of the individual's annual income, which is transformed into the real wage measured at constant prices by deflating the annual personal income in 2015, 2017, and 2018 with the consumer price index, using total annual personal income in 2013 as the base period. The independent variable X is the flexible employment mode, and  $Z_i$  is the control variable. Based on the extended Mincer income equation, the control variables that affect the income competitiveness of flexibly employed workers include individual, family, and macroeconomic factors (Oliver & Sard, 2019; Mincer & Polachek, 1974). The individual characteristics variables include gender, experience, education, health, Internet literacy, and household registration (Tian & Guo, 2021; Rodriguez-Alvarez & Rodriguez-Gutierrez, 2018). The family variables include marital status, number of children under age 18, and family economic status. Additionally, the macroeconomic control factor is GDP. Furthermore, due to uneven regional development and time differences, this study includes both regional variables and time dummy variables in the econometric model.  $Year_i$  is the time fixed effect,  $C_i$  is the area fixed effect, and  $\varepsilon_i$  constitutes the random disturbance item.

Tab. 1 – Sample variables and definitions.

Variable Type		Variable Name	Variable Definition
Dependent	Personal annual income logarithm	Lnincome	Continuous variable
Independent variables	Whether flexible employment	Flexible	1=Yes; 0=No
	Whether digital flexible employment	Digital flexible	1=Yes; 0=No
	Whether flexible self-employment	Flexible self-	1=Yes; 0=No
	Whether digital flexible self-	Digital flexible	1=Yes; 0=No
Individual factors	Gender	Gender	1=male; 0=female
	Work experience	Experience	Continuous variable



	Work experience squared	Experience <sup>2</sup>	
	Education level	Edu	0-19 continuous variable
	Health level	Health	5=very healthy; 4=relatively healthy; 3=average;
	Internet literacy	IT literacy	Whether to use the Internet daily
	Whether agricultural household	Register	1=Yes; 0=No
Family factors	Marital status	Marriage	1=married with a spouse;0=unmarried without a
	Number of children under age 18	Child18	0-5 continuous variable
	Family economic level	Festatus	5 Much higher than the average level; 4 Above the average level; 3 Average level;
Digital	Digital economy development level	Digital economy	Using the Peking University Digital Financial
Macro factors	The economic development level	GDP	Taking 2013 as the base period
Other Control variables	Region	Region	2 east; 1 middle; 0 west
	Year dummy	Year	2013; 2015; 2017; 2018

Stata 16 was used as the statistical software for empirical modeling. Firstly, this study empirically analyzes the income competitiveness of different flexible employment modes using an OLS regression model. However, gender differences in occupations and industries, as well as differences in gender roles and the gender division of labor, remain important, and research based on experimental evidence strongly suggests that discrimination cannot be discounted (Blau & Kahn, 2017). Therefore, this study also discusses the differences in income competitiveness between genders. Secondly, considering the possible endogeneity of missing variables, self-selection of individual employment modes, and unobservability in OLS estimation, it is common practice to look for instrumental variables that are correlated with employment mode variables but do not directly affect current labor force income. Using the peer mean of certain characteristics as an instrumental variable is a popular approach (Birkelund & van de Werfhorst, 2022), and this study uses the probability of flexible employment of other workers in the workers' provincial cohort as an instrumental variable for flexible employment modes, the probability of self-employment of other workers as an instrumental variable for whether the employment mode is self-employed. The generation of digital flexible employment is based on the development of the Internet, and this paper selects provincial Internet penetration as an instrumental variable for digital flexible employment, which does not directly affect individual hourly wages, thus satisfying the classical assumptions of correlation and exogeneity validity. Thirdly, to fully characterize the effects of different employment modes at different quantiles, quantile regression was used to clarify the income competitiveness differences. Finally, this study employs the extended Oaxaca-Blinder decomposition method to further explore income competitiveness differences caused by different employment modes. The differences are decomposed into variable and coefficient components, with the former representing the fraction explained by labor endowments and the latter indicating differences in income competitiveness of labor with similar characteristics due to different employment modes.

### 3.3 Data

This study uses China General Social Survey (CGSS) 2013, 2015, 2017, and 2018 data as the study sample, which is a household survey of 28 provinces in China, and comprehensively collects income and employment data on communities, households, and individuals. The study retained a valid sample of "non-farm workers" aged 16-60 years, resulting in a mixed cross-sectional data study sample of 15,929. Flexible employees are defined as "employees who have not signed a formal labor contract", "part-time employees", "individual businesses, employers who are the boss and have less than 10 employees", "freelancers", and "employees who have signed a labor contract but do not participate in basic pension insurance or basic medical insurance." At the same time, "individual businesses, employers who are the boss and have less

than 10 employees” and “freelancers”, are defined as flexible self-employment. Additionally, based on whether they use the Internet as their main source of information, flexible employment and flexible self-employment are classified as digital flexible employment and digital flexible self-employment.

#### 4. RESULTS AND DISCUSSION

Tab. 2 – Overall characteristics of the sample.

	Formal employment		Flexible employment		Traditional flexible employment		Digital flexible employment		Traditional flexible self-employment		digital flexible self-employment	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Lnincome	10.71	10.49	10.14	9.84	9.95	9.64	10.31	10.03	10.14	9.73	10.55	10.22
Experience	2.06	1.76	2.44	2.41	3.05	2.99	1.87	1.88	2.99	2.96	1.93	2.06
Edu	13.31	13.55	10.35	9.95	9.23	8.35	11.39	11.40	9.47	8.36	11.50	10.80
Health	4.05	4.07	4.03	3.94	3.94	3.86	4.11	4.01	3.96	3.84	4.11	3.99
ITliteracy	0.65	0.70	0.49	0.51	0.19	0.21	0.77	0.79	0.20	0.20	0.77	0.77
Child18	0.59	0.62	0.67	0.68	0.60	0.61	0.74	0.75	0.67	0.62	0.85	0.85
Marriage(%)	0.79	0.79	0.82	0.84	0.91	0.90	0.74	0.80	0.93	0.92	0.81	0.87
Register(%)	0.23	0.23	0.59	0.54	0.64	0.60	0.54	0.49	0.64	0.62	0.54	0.51
Observations	3585	2817	5549	3978	2669	1888	2880	2090	873	706	1112	739

Based on Tab. 2 , we find that, first, regardless of employment mode, males are more income competitive than females. Second, the income competitiveness of digital flexible employment is higher than that of traditional flexible employment, the income competitiveness of digital flexible self-employment is greater than that of traditional flexible self-employment, and the digital flexible self-employment is the highest income of the flexible employment group. Third, digital flexible employment and digital flexible self-employment present the characteristics of “younger, higher education (Shaw et al., 2022), higher self-rated health.” Fourth, flexible employment has absorbed approximately 60% of the labor force with agricultural household registration, reduced household registration barriers in employment, improved employment competitiveness and helped optimize the labor force structure.

Tab. 3 – Benchmark regression of income competitiveness across different flexible employment modes.

	Model (1)	Model (2)	Model (3)	Model (4)
Flexible employment	-0.166*** (0.019)			
Digital flexible employment		0.124*** (0.034)		
Flexible self-employment			0.253*** (0.025)	
Digital flexible self-employment				0.163*** (0.057)
Digital economy	0.007*** (0.000)	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.001)
Gender	0.269*** (0.016)	0.282*** (0.025)	0.285*** (0.024)	0.284*** (0.043)
Experience	-0.030** (0.013)	-0.032 (0.020)	-0.051*** (0.020)	-0.098*** (0.037)
Experience <sup>2</sup>	0.000	0.001	0.001	0.001

	(0.000)	(0.001)	(0.001)	(0.001)
Edu	0.054*** (0.003)	0.041*** (0.005)	0.041*** (0.005)	0.030*** (0.008)
Health	0.018* (0.010)	0.027** (0.014)	0.030** (0.014)	0.039 (0.024)
ITliteracy	0.096*** (0.019)	0.090*** (0.030)	0.128*** (0.028)	0.057 (0.052)
Register	-0.094*** (0.019)	-0.103*** (0.027)	-0.110*** (0.027)	-0.159*** (0.046)
Marriage	0.174*** (0.024)	0.234*** (0.037)	0.210*** (0.037)	0.267*** (0.070)
Child18	0.049*** (0.012)	0.047*** (0.016)	0.039** (0.016)	0.016 (0.028)
Familyfinances	0.272*** (0.012)	0.284*** (0.018)	0.265*** (0.018)	0.319*** (0.031)
GDP	-0.090*** (0.016)	-0.130*** (0.024)	-0.126*** (0.024)	-0.175*** (0.040)
2015.Year	Yes	Yes	Ye	Yes
2017.Year	Yes	Yes	Yes	Yes
2018.Year	Yes	Yes	Yes	Yes
Area	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Observations	15,929	9,527	9,527	3,430
R-squared	0.236	0.158	0.166	0.176

Notes: Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

From Tab. 3, first, the income competitiveness of flexible employees is lower than that of formal employees. The reasons could be threefold: 1) the wage of flexible employees is less stable than that of formal employees, 2) the labor relationship and social security system are not perfect, and 3) formal employees have a relatively high rate of return to education. Second, the income competitiveness of digital flexible employees is higher than that of traditional flexible employees, the income competitiveness of self-employed persons is higher than that of employed persons, and the income competitiveness of digital flexible self-employed persons is higher than that of traditional flexible self-employed persons. A possible reason is that with the vigorous development of the digital economy, digital modes of employment continue to emerge and are favored by flexible employees (Kaine & Josserand, 2019), and to a certain extent, they have improved the labor productivity of flexible employees (Henley, 2022), thereby increasing their income competitiveness. Third, education is positively correlated with income competitiveness. The income competitiveness of the married group was higher than that of the unmarried group. Fourth, males' income is more competitive. In other words, there is still a gender income gap in the context of the digital economy.

Tab. 4 – Gender differences in income competitiveness across different flexible employment modes.

	Male				Female			
Flexible employment	-	0.159*** (0.026)			-	0.181*** (0.026)		
Digital flexible employment		0.116** (0.046)				0.143*** (0.048)		
Flexible self-employment			0.249***				0.260***	



			(0.035)				(0.036)	
Digital flexible self-employment				0.180** (0.080)				0.175** (0.081)
Digital economy	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.002)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.002)
Experience	- 0.068*** (0.018)	-0.063** (0.027)	- 0.078*** (0.026)	-0.119** (0.050)	0.017 (0.019)	0.005 (0.030)	-0.022 (0.029)	-0.070 (0.055)
Experience <sup>2</sup>	0.001 (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Edu	0.050*** (0.005)	0.038*** (0.006)	0.037*** (0.006)	0.020* (0.012)	0.061*** (0.004)	0.046*** (0.006)	0.048*** (0.006)	0.041*** (0.011)
Health	0.020 (0.013)	0.029 (0.019)	0.031 (0.019)	0.014 (0.035)	0.017 (0.013)	0.027 (0.020)	0.028 (0.019)	0.068** (0.033)
itliteracy	0.105*** (0.026)	0.082* (0.042)	0.116*** (0.039)	0.029 (0.074)	0.083*** (0.027)	0.094** (0.043)	0.140*** (0.040)	0.072 (0.073)
Register	- 0.074*** (0.027)	-0.096** (0.038)	- 0.103*** (0.037)	- 0.196*** (0.064)	- 0.115*** (0.026)	- 0.103*** (0.038)	- 0.114*** (0.038)	-0.107* (0.064)
Marriage	0.275*** (0.034)	0.315*** (0.051)	0.292*** (0.051)	0.357*** (0.096)	0.048 (0.033)	0.127** (0.052)	0.103** (0.052)	0.127 (0.101)
Child18	0.053*** (0.016)	0.057** (0.023)	0.046** (0.023)	0.001 (0.038)	0.043*** (0.016)	0.034 (0.024)	0.030 (0.024)	0.033 (0.040)
Familyfinances	0.286*** (0.017)	0.295*** (0.024)	0.273*** (0.025)	0.348*** (0.044)	0.252*** (0.017)	0.266*** (0.026)	0.253*** (0.026)	0.279*** (0.044)
Gdp	- 0.083*** (0.023)	- 0.124*** (0.034)	- 0.114*** (0.033)	- 0.151*** (0.056)	- 0.098*** (0.022)	- 0.133*** (0.034)	- 0.139*** (0.034)	- 0.207*** (0.056)
2015.Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2017.Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2018.Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,134	5,549	5,549	1,985	6,795	3,978	3,978	1,445
R-squared	0.211	0.149	0.155	0.149	0.265	0.157	0.166	0.190

Notes: Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Judging from the regression results in Tab. 4, those in formal employment are more income-competitive than those in flexible employment, regardless of gender. Furthermore, the income competitiveness of females engaged in digital flexible employment, self-employment, and digital flexible self-employment is higher than that of females engaged in traditional flexible employment, employed, and traditional flexible self-employment, and their income has increased faster than that of males. Among them, the income of females in digital flexible employment is 2% higher than that of males in digital flexible employment, and the income of females in digital flexible self-employment is 2% higher than that of males in digital flexible self-employment. In other words, digital employment modes are more competitive in terms of income, especially for females. Moreover, the digital economy affects the income competitiveness of flexible workers, digital flexible employment, and flexible self-employed workers, and access to education increases income competitiveness regardless of gender. Finally, the income competitiveness of married males is higher than that of unmarried males,

but the income competitiveness of married females is not higher than that of unmarried females. This disparity may be because the rapid development of the digital economy has accelerated the pace of life and increased family life pressures. For married females, non-work commitments such as family constrain women more than men (Churchill & Craig, 2019), which will have a penalty effect on female income competitiveness. While for married males, it will further increase their sense of family responsibility and increase their income competitiveness relative to unmarried males.

Tab. 5 – Instrumental variable regression results (2SLS)

	Flexible employment	Inincome	Digital flexible employment	Inincome	Flexible self-employment	Inincome	Digital flexible self-employment	Inincome
Flexible employment rate	0.543*** (0.046)							
Flexible employment		- 0.928*** (0.212)						
Internet penetration			0.317*** (0.076)				0.314** (0.124)	
Digital flexible employment				1.212* (0.827)				
Self-employment rate					0.643*** (0.100)			
Flexible self-employment						0.765*** (0.287)		
Digital flexible self-employment								1.585*** (0.390)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM	134.373		17.158		79.580		53.133	
Chi-sq(1) P-val	0.0000		0.0000		0.0000		0.0000	
CD Wald-F	38.704		19.075		88.543		53.067	
KP Wald-F	138.744		17.285		80.822		53.332	

Notes: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

From Tab. 5, the Wald-F statistic and the KP Wald-F statistic, both of which are greater than the Stock-Yogo test of 16.38 at the 10% level, do not have a weak instrumental variable problem and prove the validity of the instrumental variables in this paper. The regression results of the instrumental variables are consistent with the baseline regression results (Tab. 3 and 4), thus indicating that the baseline regression results are robust.

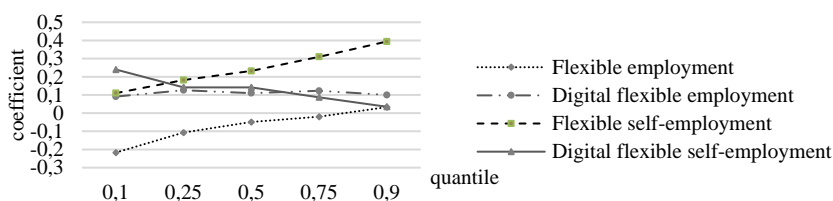


Fig. 2 – Quantile regression of income competitiveness across different flexible employment modes.

According to Fig. 2, first, in the low- and middle-income quantiles (0.1, 0.25, and 0.5), the income competitiveness of the flexibly employed is lower than that of the formally employed (Conover et al., 2022; Goncalves & Martins, 2020). Second, at the 0.1-0.9 quantile, digital flexible workers are more income competitive than traditional flexible workers, and flexible self-employed workers are more income competitive than flexible-employed workers (Sorgner et al., 2017). Third, for digital flexible self-employed workers, their income competitiveness is higher than that of traditional flexible self-employed workers in the low- and middle-income quantiles, but not in the high 0.9 income quantile. This difference may be because traditional flexible self-employed workers in the higher income quantile have already occupied a certain market base and developed certain brand effects and economies of scale in the market, and therefore have higher income competitiveness.

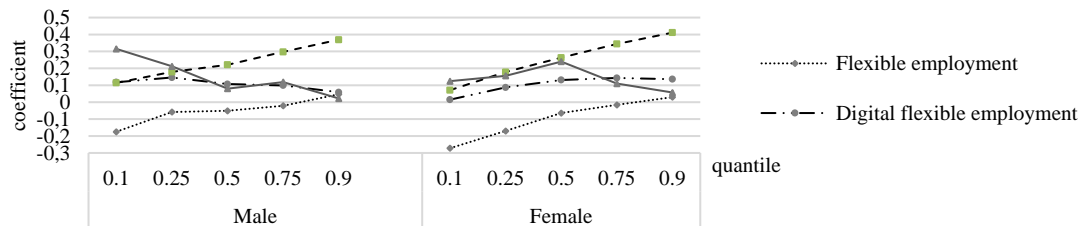


Fig. 3 – Gender difference in quantile regression of income competitiveness across different flexible employment modes.

In Fig. 3, it can be seen that for males in flexible employment, their income competitiveness is lower than that of those in formal employment at the low- and middle-income quantiles (0.1, 0.25, 0.5), but not at the high-income quantile (0.75, 0.9), and the same is for female. In other words, flexible employment in the lower income quantile is at a relative disadvantage in terms of income competitiveness relative to formal employment, but entry into digital flexible employment and flexible self-employment is significant for income improvement (Ilsoe et al., 2021), and higher income competitiveness.

As there are differences in social security between workers with and without a labor contract (Suleman & Figueiredo, 2018), this study excludes flexible workers without written contracts from the total sample (Tab. 6).

Tab. 6 – The income competitiveness of flexible workers who have signed labor contracts.

	Model (1)	Model (2)	Model (3)	Model (4)
Flexible employment	0.003 (0.021)			
Digital flexible employment		0.160*** (0.052)		
Flexible self-employment			0.206*** (0.048)	
Digital flexible self-employment				0.246** (0.105)
Digital economy	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.004 (0.003)
Control	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Observations	6,599	1,472	1,472	308
R-squared	0.368	0.372	0.376	0.442



Notes: Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

As shown in Tab. 6, for flexible employment with a contract, their income competitiveness is lower than that of formally employed workers in the low-income quantile (0.1). However, at

the high-income quantile (0.9), flexible workers have higher income competitiveness than formally employed workers at the 1% significance level. This difference may be because flexibly employed people with contracts enjoy the same level of public social resources as those who are formally employed, as well as a more comprehensive system of rights and benefits protection. In terms of internal differences, the tab. 6 results were consistent with the Benchmark regression results.

Tab. 7 – O-B decomposition results of income competitiveness.

		Flexible employment	Digital flexible employment	Flexible self-employment	Digital flexible self-employment
Full sample	Total difference	0.5976	-0.3723	-0.3001	-0.4631
	Variable differences	0.4204	-0.1656	-0.0507	-0.1899
	Coefficient difference	0.1772	-0.2067	-0.2493	-0.2733
Male	Total difference	0.5727	-0.3578	-0.3654	-0.4101
	Variable differences	0.4083	-0.1080	-0.1197	-0.0884
	Coefficient difference	0.1644	-0.2499	-0.2457	-0.3217
Female	Total difference	0.6443	-0.3968	-0.2137	-0.4930
	Variable differences	0.4469	-0.2358	0.0340	-0.2619
	Coefficient difference	0.1974	-0.1610	-0.2476	-0.2311

From Tab. 7, the income competitiveness of the formally employed is six percentage points higher than that of the flexibly employed, with the variable differences accounting for 70.35% of the total difference and the coefficient differences accounting for 29.65%. This signifies that 69.90% of the income competitiveness difference between formal employment and flexible employment is caused by differences in human capital characteristics, and the other 30.10% caused by the different modes of employment. In terms of gender differences, the income competitiveness gap between female formal employees and female flexible employees is larger, and the proportion caused by the coefficient difference is higher. In other words, with the digital economy, there is still a degree of labor market segmentation and occupational segregation (Hara, 2018) in the labor market in China, which is even more serious for females.

The income competitiveness of those in digital flexible employment is 37.23% higher than that of those in traditional flexible employment. For females, the digital economy makes the income competitiveness of those in digital flexible employment nearly four percentage higher than that of females in traditional flexible employment. Besides, the income competitiveness of self-employed workers is three percentage higher than that of employed workers, and the income competitiveness of digital flexible self-employed workers is nearly five percentage higher than that of traditional flexible self-employed workers. Meanwhile, the income competitiveness of males in digital flexible self-employment is 41.01% higher than that of males in traditional self-employment, and the income competitiveness of females in digital flexible self-employment is 49.30% higher than that of females in traditional self-employment. This further validates that the digital flexible employment modes can assist women in overcoming gender segregation in some occupations and industries (Churchill & Craig, 2019), and have a significant increase in female income competitiveness.

## 5. CONCLUSION

This study examines the income competitiveness differences of different flexible employment modes in the context of the digital economy from both theoretical and empirical perspectives, drawing three conclusions. First, engaging in digital flexible employment has higher income competitiveness. Based on Tabs. 2, 3 and 5, the empirical results confirm that the income competitiveness of the flexibly employed is lower than that of the formally employed, but in the flexible employment market, the income competitiveness of the digital flexibly employed is higher than that of the traditionally flexibly employed, the income competitiveness of the

digital flexibly self-employed is higher than that of the traditionally flexibly self-employed, and the income competitiveness of the self-employed is higher than that of the employed, confirming Hypothesis 1. Digital technology has led to the emergence of digital modes of flexible work (Rani & Furrer, 2021), and digital employment modes have enriched the employment methods of workers and reduced the unemployment rate owing to their low entry costs, flexibility, and diversity (Lederman & Zouaidi, 2022). This study considers digital flexible employment in the future as a new momentum to improve labor productivity and income competitiveness, it is also the trend of flexible employment in the labor market.

Second, females have higher income competitiveness in digital flexible employment modes. Females engaged in digital flexible employment and digital flexible self-employment have higher income competitiveness than those engaged in traditional flexible employment, and also have higher income growth than males (Tab. 4, and Fig. 3). Hypothesis 2 is confirmed. This suggests that the gender income gap between different employment modes still exists in the context of digital flexible employment (Barth et al., 2021), but that digital flexible employment exhibits characteristics of flexibility in the employment relationship, flexibility in the scheduling of work, and flexibility in work locations (Spreitzer et al., 2017), which helps alleviate females' reproductive penalties and attenuates gender occupational segregation in the labor market; therefore, this study agrees that connecting with digitalization, enhancing females' digital employment skills in the context of the digital economy, is an important way to improve income competitiveness.

Third, digital flexible employment increases income competitiveness while also exacerbating the polarization of the flexible employment market. Quantile regressions and income gap decomposition (Fig. 2, Tabs. 6, 7) find that the wage penalty for flexible employment is substantially higher for individuals at the bottom of the wage distribution, and this study also supports the hypothesis of a two-tier structure of the flexible employment labor market (Liwiński, 2022), which may increase the internal income gap of flexible workers and exacerbate income polarization. Hypothesis 3 holds. Therefore, this study argues that public policies should target vulnerable groups of flexible workers with low human capital levels and low incomes, provide training on digital skills, and increase opportunities for digital employment modes to improve their income competitiveness, which is an important breakthrough to achieve prosperity and sharing.

However, this study has certain limitations. It lacks individual international microdata, and future research should use international data for comparative analysis to draw more reliable conclusions. Furthermore, the factors and mechanisms affecting income competitiveness are complex; therefore, future researchers should adopt causal models to better understand these variables.

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#### Contact information

##### **Prof. Kangyin Lu, Ph.D.**

Northeast Normal University  
School of Business  
P. R. China  
E-mail: [luky440@nenu.edu.cn](mailto:luky440@nenu.edu.cn)  
ORCID: 0000-0002-0698-1327

##### **Liwen Jia, Ph.D. Candidate (Corresponding Author)**

Northeast Normal University  
School of Business  
P. R. China  
E-mail: [jialw328@nenu.edu.cn](mailto:jialw328@nenu.edu.cn)  
ORCID: 0000-0002-7103-9821

##### **Si Chen, Ph.D. Candidate**

Northeast Normal University  
School of Business  
P. R. China  
E-mail: [chens501@nenu.edu.cn](mailto:chens501@nenu.edu.cn)  
ORCID: 0000-0001-8013-5973