The Impact of E-commerce on Regional Labor Market in the Era of Digital Economy: A Case Study of Employment in Internet-related Industries in China

Hanyan Li[1]; Warattaya Chinnakum[2]; Supanika Leurcharusmee[3]

[1,2,3]Faculty of Economics, Chiang Mai University, Chiang Mai, 50200, Thailand

Corresponding Author Email: hanyanli831@gmail.com

Abstract— This study focuses on the impact of the digital economy on the regional labor market in China, and explores how digital economic activities such as e-commerce shape employment patterns in Internet-related industries from 2014 to 2023, combined with empirical analysis in the eastern, central, western, and northeastern regions. It is found that due to the mature development of the e-commerce industry in the eastern region, the direct promotion effect of e-commerce activities on employment is limited, while the expansion of the service industry significantly promotes the employment growth. E-commerce purchasing and sales activities in the central region showed a strong job-boosting effect, indicating that the digital economy has greater potential in developing regions. However, digital economic activity in the western and northeastern regions has a weak role in promoting employment, and even shows a negative correlation on some indicators, which may be related to regional differences in economic structure, industrial digitization level and technology application. Overall, the impact of the digital economy on the labor market has significant regional heterogeneity, indicating the need for differentiated policies for different regions to balance regional economic development and optimize the structural impact of the digital economy on the labor market.

Keywords: Digital economy, Labor market, Regional heterogeneity, E-Commerce, Chinese economy

I. INTRODUCTION

Digital economy is a new economic form developed based on information and communication technology (ICT), covering e-commerce, Internet finance, cloud computing, big data, artificial intelligence and other fields. China's digital economy covers multiple links from digital infrastructure to online consumption and smart manufacturing. In 1994, China was officially connected to the Internet, marking the beginning of the information age in China. With the introduction of the Internet, portals, E-mail and instant messaging tools are gradually popularized. The rise of e-commerce and social media, the rapid development of e-commerce: Alibaba was founded in 1999 and launched platforms such as Taobao and Alipay, which gradually laid the foundation of e-commerce in China(Li Guomin et al., 2019).E-commerce platforms such as JD.com have also risen. By 2010, the popularity of mobile Internet and smart devices The explosion of mobile Internet: promoted the rise of online consumption, mobile payments and the sharing economy(Wang Junling et al., 2020).

The digital economy is closely linked to the labor market, with technologies such as automation and artificial intelligence replacing low-skilled jobs and driving the transition of the workforce to high-skilled jobs, which can reshape employment patterns(Chui, M, Manyika, J et al., 2016).The surge in demand for high-skilled jobs (such as data analytics, e-commerce, etc.) and the decline of low-skilled jobs have led to structural imbalances in the labor market. Regarding the dual impact of technological progress on employment stability and labor market operation, and the digital economy has both positive effects on employment and challenges(Li Yingfu et al., 2019).Therefore, it is important to study the relationship between the digital economy and the labor market to facilitate policy formulation, address unemployment and skills mismatch, and promote balanced regional economic development.

China has the world's largest population of Internet users, and an active consumer base has driven the rapid development of the digital economy. Growing consumer demand in areas such as e-commerce, social media, and digital entertainment is fueling the growth of the digital economy. China has made remarkable progress in technological innovation in 5G, artificial intelligence, cloud computing and other fields, which has promoted the continuous upgrading of the digital economy. These technologies not only promote the development of emerging industries, but also promote the digital transformation of traditional industries(Brynjolfsson, E et al., 2017).With the further popularization of digital technologies, the digital economy will continue to influence the structure and development of regional economies and labor markets, and have a profound impact on the global digital economic landscape(Zhang Chao, 2022).

II. LITERATURE REVIEW

Through combing the existing research results, we can find that the concept of digital economy can be traced back to 1996. Don Tapscott first coined the term "digital economy" in his book The Digital Economy: Promise and Risk in the Age of Intellectual Connectivity, emphasizing the importance of the Internet in driving the development of e-commerce. Moulton (1999) pointed out that there is no universal definition of the digital economy, and the digital economy he mentioned in the article covers not only information technology but also e-commerce.The digital economy can be divided into two parts: the digital transformation of the industry and the development of digital industrialization. Through digital transformation, traditional industries can achieve economies of scale and scope, improve the efficiency of resource allocation (Yan Chun et al., 2019)

Wang Wen (2021) pointed out through the study of panel data that the technological progress promoted by the digital economy reduces the employment demand of the manufacturing industry, while increasing the employment demand of modern high-end service industries such as knowledge-intensive and service-intensive, which promotes the structural optimization and upgrading of China's labor market and promotes the development of high-quality employment. Ding Lin and Wang Huijuan (2020) discussed the impact of the development of Internet technology on China's employment structure, and found that Internet technology significantly promoted the employment of the tertiary industry, while significantly inhibited the employment of the primary industry.

The impact of the digital economy is driving changes in the labor market. The formation of the digital economy not only stems from the rapid development of digital technology, but also from the popularity of remote employment mode accelerated by the global epidemic. As the Internet economy is booming around the world, more and more countries are joining this transformation, gradually breaking traditional production, employment and consumption patterns. (Morozova, N. N, 2021).

The job market and workers themselves will be affected by the digital economy. Studies have shown that the digital economy has both positive and negative effects on employment. The positive impact is to expand the scale of employment and increase employment opportunities.(Jia Zhuoqiang, 2023).

III. METHODOLOGY

We chose this model because BLRM is a powerful algorithm for sampling from complex posterior distributions,In particular, the Bayesian framework is used to improve the flexibility of parameter estimation, especially in the case of small samples or unbalanced data(Geliman, A et al., 2006), and it is capable of handling models that contain multiple variables and complex relationships.Take advantages of Bayesian methods for complex models and uncertainty assessment (Kruschke, J. K. (2014),Analyzing the relationship between digital economy development and labor market in the four regions may involve multiple variables, non-linear relationships and heterogeneity, and these complexities can be better addressed by BLRM.

MCMCregress utilizes standard Gibbs sampling to simulate from the posterior distribution, involving a multivariate Normal draw for the betas and an inverse Gamma draw for the conditional error variance. To ensure maximum efficiency, the actual simulation is carried out using compiled C++ code. (Andrew D. Martin et al., 2011). equation can be expressed as:

$$\text{Log}(inemp_i)=\beta_0+\beta_1.ecs_i+\beta_2.ecp_i+\beta_3.gdp_i+\beta_4.pcdi_i+\beta_5.ati_i+\epsilon_i \quad (1)$$

$inemp_i$ is number of employment in Internet-related industries in the i region (which may be logarithmic to reduce heteroscedasticity),ecp_i is e-commerce purchases in the region, ecs_i is e-commerce sales in the region,$gdp_i$is GDP in the region, $pcdi_i$ is disposable income per capita in the region,$ati_i$is value added of the tertiary industry in the region,$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$is the regression coefficient to be estimated. ϵ_i is error term is usually assumed to follow a normal distribution.

OLS model plays a benchmark role in comparing complex models (Wooldridge, J. M, 2020). Therefore, adding OLS model can provide a benchmark for complex models (such as BMLR, etc.) and help evaluate the improvement degree of new models compared with traditional methods.The equation can be expressed as:

$$Yit=\beta 0+\beta 1EC\_Purchaseit+\beta 2EC\_salesit+\beta 3GDPit+\beta 4Tiit+\beta 5Incomeit+\varepsilon it \quad (2)$$

Through the application of OLS in microeconomic research, especially the use cases in policy evaluation and labor market analysis, its ease of use and interpretability in practical analysis were found (Cameron, A. C. et al., 2022). The parameter estimation of OLS model has clear economic meaning, which is easy to interpret the results and put forward policy recommendations. Stock and Watson(2020) explore the use of OLS in economic forecasting and compare it to modern techniques such as machine learning and Bayesian methods. As one of the most commonly used regression methods, OLS provides comparability for studies, allowing other researchers to verify and compare results.

IV. EMPIRICAL ANALYSIS

In the BLRM model analysis of the eastern region, e-commerce purchases (eecs) : the posterior mean is 0.01671, indicating that procurement activities have a promoting effect on employment. E-commerce sales volume (eecp) : A posterior mean of -0.12684 may suggest a complex or inverse relationship between sales activity and employment.

Table1:Bayesian Statistics of Digital Economy Eastern-Central Regions

Variables	Mean	SD	[2.5%	97.5%]
Eastern Part				
(Intercept)	0.07818	0.7088	-1.312	1.475
Eecs	0.01671	3.0119	-5.8986	6.005
Eecp	-0.12684	2.4783	-5.0246	4.681
Epcdi	-0.02599	3.1172	-6.0785	6.092
Eati	0.02866	2.9773	-5.8275	5.889
Egdp	0.035	3.0855	-6.1002	6.099
Sigma2	1.74599	0.7823	0.8009	3.724
Middle Part				
(intercept)	0.03321	0.7538	-1.4421	1.522
Mecs	0.05039	2.9418	-5.7723	5.874
Mecp	0.05638	2.259	-4.3716	4.461
Mpcdi	-0.05592	3.1323	-6.202	6.07
Mati	-0.04866	2.9947	-5.9512	5.776
Mgdp	-0.00626	2.5315	-5.0934	4.993
Sigma2	1.80527	0.8171	0.8257	3.854

Source: Author's Calculation

In the BLRM analysis of the middle region model, there is a significant positive effect: e-commerce purchase volume (mecs, mean 0.05039) and sales volume (mecp, mean 0.05638) have a positive effect on employment. The mean value of the residual variance ($sigma^2$) of the model is 1.80527, indicating high stability. Overall, e-commerce activities have a significant positive impact on the employment of Internet-related industries in the central region.

Table2:Bayesian Statistics of Digital Economy Western-Northern Regions

Variables	Mean	SD	[2.5%	97.5%]
Western Part				
(Intercept)	0.0410017	0.7422	-1.415	1.507
Wecs	0.0017691	2.6536	-5.2653	5.258
Wecp	-0.0100361	1.2034	-2.404	2.383
Wpcdi	-0.0322448	3.1176	-6.1347	6.106
Wati	-0.0008078	3.0413	-6.0069	5.988
Wgdp	-0.014245	3.1255	-6.1957	6.071
Sigma2	1.8389827	0.8523	0.8281	4.009

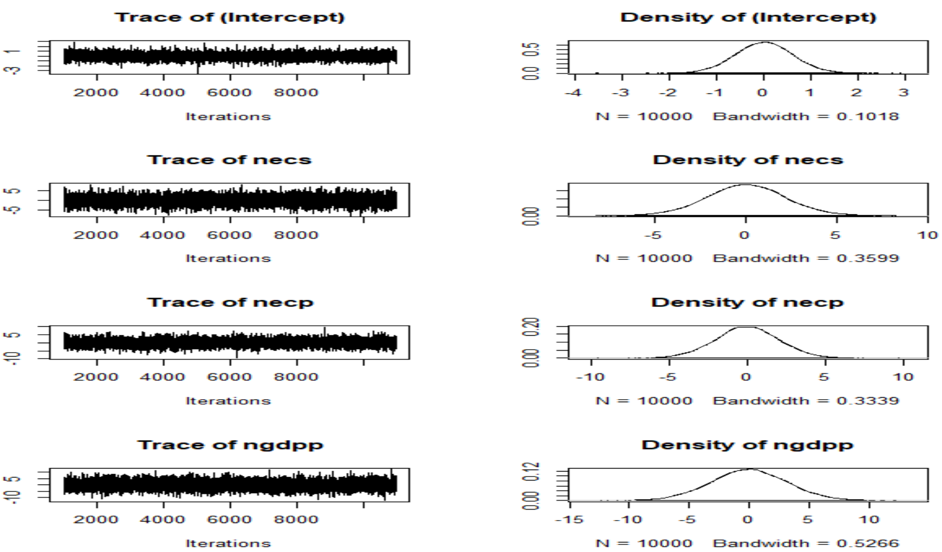
Northern Part				
(Intercept)	-0.006397	0.6197	-1.2201	1.22
Necs	0.02719	2.166	-4.2887	4.288
Necp	-0.016616	2.0222	-4.0248	3.948
Npcdi	-0.03581	3.1345	-6.1469	6.076
Nati	0.012543	3.1005	-6.0755	6.146
Ngdp	-0.036184	3.1363	-6.3075	6.146
sigma2	1.825034	0.8341	0.8231	3.955

Source: Author's Calculations

In the BLRM western region model analysis. The influence of e-commerce purchase volume (wecs) on employment is positive (mean value: 0.0018). The posterior mean of e-commerce Sales volume (wecp) is negative (-0.0100), indicating that sales activity may have a slight negative impact on employment. The model is well fitted (sigma² posterior mean is 1.839).

In the BLRM model analysis of Northeast China, the posterior mean of e-commerce purchase volume (necs) and e-commerce sales volume (necp) necs is positive (0.027190), indicating that e-commerce purchase volume may have a slightly positive impact on the number of employees in Internet-related industries, while e-commerce sales volume may have a slightly negative impact on the number of employees. (sigma² = 1.825). The standard error is 0.008341, indicating that the estimate of error is relatively stable.

Figure1:MCMC (Markov Chain Monte Carlo) sampling result of Bayesian model



In the above picture description, the Intercept trajectory diagram shows that the sampling of the intercept term is stable, and the density diagram shows that the posterior distribution is close to normal distribution. The intercept term reflects the base level of the dependent variable if all independent and control variables are zero. The necs trace shows that the sampling chain of the coefficient has converged, and the density map shows the posterior distribution. The positive and negative values and magnitude of the coefficient can explain the intensity and direction of the influence of regional e-commerce purchases on the number of employment in Internet-related industries. necp is similar to necs in that the sampling of this coefficient is stable and the density plot shows the posterior distribution. The size and direction of this coefficient also reveal the impact of regional e-commerce sales on employment. The ngdpp trace plot and density plot show the sampling stability and posterior distribution of the coefficient. The significance of this control variable coefficient is to adjust the impact of the overall economic size of the region on the number of employment in Internet-related industries.

Taken as a whole, these charts show the stability of the MCMC sample and the posterior estimation distribution of each variable to the dependent variable. According to the positive and negative and significance of these coefficients, the specific impact of each variable on employment in regional Internet-related industries can be judged.

Table4:OLS estimation of digital economy in four regions

Variables	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Einem-part						
Eecs	-0.9129505	1.087639	-0.84	0.463	-4.374303	2.548402
Eecp	-0.3149633	0.3428081	-0.92	0.426	-1.405932	0.776005
Epcdi	-5.185544	4.320535	-1.2	0.316	-18.93542	8.564328
Eati	1.313656	1.873019	0.7	0.534	-4.647127	7.274438
Egdp	2.982463	2.042765	1.46	0.24	-3.518527	9.483454
_cons	0.2559716	0.1818845	1.41	0.254	-0.3228662	0.8348093
Minem-part						
Mecs	0.3789805	0.8543643	0.44	0.687	-2.339988	3.097949
Mecp	0.264368	0.3250585	0.81	0.476	-0.7701132	1.298849
Mpcdi	0.4160241	6.576647	0.06	0.954	-20.5138	21.34585
Mati	-1.138367	2.505484	-0.45	0.68	-9.111933	6.8352
Mgdp	-0.1747132	0.2032911	-0.86	0.453	-0.8216762	0.4722499
_cons	0.0535391	0.3927043	0.14	0.9	-1.196221	1.303299
Winem-part						
Wecs	-0.0191102	0.1641388	-0.12	0.915	-0.5414731	0.5032526
Wecp	-0.0060755	0.0502039	-0.12	0.911	-0.1658468	0.1536958
Wpcdi	0.2685511	0.7562309	0.36	0.746	-0.2138113	2.675215
Wati	-0.3359303	0.4448866	-0.76	0.505	-1.751758	1.079897
Wgdp	-0.2488787	0.4880031	-0.51	0.645	-1.801922	1.304165
_cons	0.0721335	0.0534589	1.35	0.27	-0.0979967	0.2422637
Ninem-part						
Necs	0.1008018	0.2053051	0.49	0.657	-0.5525705	0.7541742
Necp	0.0557007	0.2209169	0.25	0.817	-0.6473553	0.7887568
Npcdi	0.0760833	3.26144	0.02	0.983	-10.30327	10.45544
Nati	0.036088	2.135293	0.02	0.988	-6.759368	6.831544
Ngdp	-1.091932	1.748423	-0.62	0.577	-6.656194	4.47233
_cons	0.0074694	0.100764	0.07	0.946	-0.3132066	0.3281454

Source: Author's Calculations

OLS Eastern Region: The e-commerce procurement coefficient is -0.9129, meaning that for every 1% increase in e-commerce purchases, employment in Internet-related industries may be reduced by about 0.91%. For every 1 percent increase in e-commerce sales, employment may decrease by about 0.31 percent. This may be because the e-commerce industry has matured and is more inclined to reduce its reliance on labor through technology and efficiency improvements.

OLS Middle Region: The effect of e-commerce procurement on employment in Internet-related industries is positive, with a coefficient of 0.3789, indicating that every 1% increase in e-commerce procurement may increase employment in Internet-related industries by about 0.38%. This shows the positive role of e-commerce procurement activities in promoting employment in the central region. The positive effect of e-commerce sales is slightly smaller than that of e-commerce purchases, with a coefficient of 0.2644, indicating that for every 1% increase in e-commerce sales, employment in Internet-related industries may increase by about 0.26%.

OLS Western region: For every 1% increase in e-commerce purchases, employment in Internet-related industries may decrease by about 0.02%. E-commerce sales, with a coefficient of -0.0061, indicate that a 1% increase in e-commerce sales may reduce employment by about 0.006%.

OLS Northeast region: The e-commerce procurement coefficient is 0.1008, indicating that for every 1% increase in e-commerce purchases, employment in Internet-related industries may increase by about 0.10%. The e-commerce sales coefficient is 0.0557, indicating that a 1% increase in e-commerce sales may increase employment in Internet-related industries by about 0.06%.

V. CONCLUSION

Through empirical analysis of labor markets in different regions of China, this study reveals the multi-dimensional impact of digital economy in promoting employment and reshaping labor market structure. The study found that e-commerce procurement and sales activities in the eastern region have limited direct pull effect on employment, which may reflect the mature development stage of the e-commerce industry in the region, which relies more on technological advances and automation to improve efficiency and reduce reliance on labor. At the same time, the growth of the tertiary industry significantly boosted employment in related industries, indicating that the expansion of the service industry is still an important engine to promote employment. The central region showed a strong employment promotion effect, and e-commerce procurement and sales activities significantly promoted the growth of employment in Internet-related industries, which indicates that the digital economy still has a large employment potential for developing regions, especially under the combined effect of industrial expansion and consumer demand.

In contrast, the impact of digital economy development on employment in western and northeast China is relatively limited or even negative, especially e-commerce sales activities and regional economic growth have no significant driving effect on employment. This may be related to the capital-intensive economic structure of the two places, the relatively lagging industrial upgrading, and the imperfect digital economic ecosystem. However, the increase in residents' income has had a positive impact on employment to a certain extent, indicating that consumption upgrading and demand growth can be an important way to stimulate employment. It is worth noting that the impact of tertiary industry value added and regional GDP shows a negative correlation in the western and northeastern regions, which may reflect the displacement effect of automation and digitalization processes on traditional jobs.

In general, there is significant regional heterogeneity in the impact of digital economy on China's regional labor market, which reflects the differences in economic development level, industrial structure, technology application and policy support in different regions. This study provides an important practical reference for policy makers, indicating that it is necessary to formulate digital economy development strategies according to local conditions: the eastern region should further promote technological innovation and industrial upgrading, and strengthen the training of high-skill positions; The central region can unlock the employment potential of the digital economy by optimizing e-commerce infrastructure and expanding market demand; The western and northeastern regions need to strengthen the construction of digital infrastructure and accelerate the digital transformation of industries, so as to fully tap the role of the digital economy in promoting employment, and properly cope with the structural unemployment challenges brought about by technological progress. These strategies will not only help promote balanced regional economic development, but also lay the foundation for building a more inclusive digital economic ecosystem.

VI. ACKNOWLEDGEMENTS

First author would like to thank Dr.Warattaya Chinnakum and Dr.Supanika Leurcharusmee for their supervision on completing this work.

REFERENCES

1. Siddhartha Chib. 1995. “Marginal Likelihood from the Gibbs Output.” Journal of the American Statistical Association. 90: 1313-1321.
2. Jia Zhuoqiang.(2023). Research on the impact of Digital Economy on Labor and Employment (Ph. D. Dissertation, Sichuan University). Learned scholar
3. Morozova, N. N. (2021). The Impact of the Digital Economy on the Tansformation of the Labor Market. (4), 426-434.

4. Wang Wen. Does industrial intelligence promote high-quality employment in the era of digital economy [J]. Economist,2020(04):89-98.

5. Ding Lin, Wang Huijuan. The influence of the Internet technology progress on China's employment and national comparative study [J]. Journal of economics, 2020 (01): 72-85.

6. Yan Chun, Ding Yi, Liu Xinhong. Spatial correlation of digital economy and its interaction with real economy [J]. China Circulation Economy, 2019, 38 (4) : 13-25.

7. Brent R. Moulton. GDP and the Digital Economy : Keeping up with the Changes [J].Understanding the Digital Economy Data.1999.4(5).34-48.

8. Li Guomin, Zhang Ling. (2019). Integrated development model of Internet Finance and E-commerce. Science, Technology and Economy, 2019(2), 72-79.

9. Wang Junling, & Wang Qi. (2020). The rapid development of China's e-commerce in the era of digital economy and its impact. Modern economic management, 2020 (4), 12-16. https://doi.org/10.3969/j.issn.1006-8340.2020.04.003

10. Zhang Chao. (2022). An Empirical study on the influence of digital economy level on labor Marketization (Master's Thesis). Jiangxi University of Finance and Economics.

11. Li Yingfu, & Feng Jun. (2019). Review on Digital economy and Labor Market. Enterprise Reform and Management, 2019(19), 5-7.

12. Brynjolfsson, E., & McAfee, A. (2017). Harnessing our digital future. Foreign Affairs, 96(4), 10-20.

13. Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—and where they can't (yet). McKinsey Quarterly.

14. Andrew D. Martin, Kevin M. Quinn, and Jong Hee Park. 2011. "MCMCpack: Markov Chain Monte Carlo in R.", Journal of Statistical Software. 42(9): 1-21. doi:10.18637/jss.v042.i09.

15. Kruschke, J. K. (2014). Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan. Academic Press.

16. Gelman, A., & Hill, J. (2006). Data analysis using regression and multilevel/hierarchical models. Cambridge University Press.

17. Wooldridge, J. M. (2020). Introductory econometrics: A modern approach (7th ed.). Cengage Learning.

18. Stock, J. H., & Watson, M. W. (2020). Introduction to econometrics (4th ed.). Pearson.

19. Cameron, A. C., & Trivedi, P. K. (2022). Microeconometrics: Methods and applications. Cambridge University Press.