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The Impact of the Omicron Epidemic on Employment in China

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Abstract

Under the background of the new normal of the epidemic, the Omicron epidemic from March 2022 has greatly impacted China' s macro economy, and also has a great impact on China' s employment situation. Firstly, through combing the theoretical mechanism and the current situation, this paper believes that the Omicron epidemic will have an impact on employment in China by aggravating the two paths of frictional unemployment and structural unemployment. Then, through the qualitative way of statistical data comparison and the quantitative way of DID model, this paper obtained the following conclusions : (1) The Omicron epidemic has a significant negative impact on employment in China. (2)The negative impact of the Omicron epidemic on employment in big cities is higher than the national average level. (3)The Omicron epidemic has a greater negative impact on the employment of young groups such as current graduates. Finally, this paper puts forward relevant policy recommendations.

Keywords

COVID-19, Omicron, Employment, Unemployment Rate.

1. Introduction

Under the ongoing impact of the COVID-19 epidemic, the large-scale outbreak of its variant Omicron since March 2022 has brought a new wave of impact to China. In January 2022, the first cases of infection were detected in Tianjin, followed by Shenzhen, Shandong, and Fujian, and in March, the outbreak started in Shanghai and spilled over to other provinces and cities, opening a new outbreak pattern. The outbreak started in Shanghai in March and spilled over to other provinces and cities, starting a new outbreak pattern. The Omicron epidemic is characterized by a wide range of infections and a deep impact.

In Shanghai, for example, the current round of the epidemic has brought the mega-city to a standstill for nearly 2 months, with closed management policies disrupting parts of the supply chain, depressing the normal conduct of national trade and international investment, putting many SMEs on the verge of bankruptcy, and shrinking the supply of services. In a chain reaction, the country's unemployment rate gradually climbed, with the national urban survey unemployment rate rising to 6.1% in April 2022, up 1 percentage point year-on-year and the second highest level since the outbreak in 2020 (6.2% in February 2020). The Omicron epidemic, as a catalyst for frictional and structural unemployment, has greatly impacted the country's job market at this stage.

Under the continuous effect of the epidemic, the study of the impact of the Omicron epidemic on employment can, on the one hand, explore the extent to which a new epidemic shock will adversely affect China's job market under the normalization of the epidemic, and on the other hand, assess whether the relevant policy measures taken by China in the face of the epidemic can effectively curb the continuous rise of unemployment rate in the face of the epidemic shock.

Therefore, the core issue of this paper, "the impact of the Omicron epidemic on employment", has a strong practical significance.

2. Literature Review

2.1. The Omicron epidemic's impact on Macroeconomics

Many scholars have focused on the impact of the Omicron epidemic on various sectors of the Chinese macroeconomy. Using an improved multi-regional general equilibrium model for China, Wu Feng et al. (2021) measure that at the macroeconomic level during the epidemic, China's GDP is in a loss situation compared to the norm, and short-term consumption and closure levels fall and prices rise [1]. Wang Jianfeng and Wang Weili (2022) apply the GTAP model to assess the different impacts of long-term persistence of the epidemic and short-term epidemic on macroeconomic sectors, with long-term small-scale epidemics generating significant shocks to China's GDP, import/export trade, residents' welfare, and sectoral output, while the negative impacts of short-term chance outbreaks will be offset by the resilience originating from economic development [2]. From the perspective of the BGG-DSGE model, Shi Benye and Yang Shanran (2021) found that the Omicron epidemic would have an impact on consumption, savings investment, output, interest rates, capital goods market, and labor market through the contradiction between residents' income and consumption demand, between labor demand and investment level, and between capital demand and firm's financial position [3]. Based on a dynamic stochastic general equilibrium model, Wu Liyuan and Liu Yanzhao (2021) demonstrate the characteristic fact that China's consumption has declined more than production investment and recovered more slowly since the epidemic [4]. Zhang Youguo et al. (2021) decompose the economic impact of the new crown epidemic and argue that the epidemic significantly affects GDP growth, and that, in terms of policy, stable employment and moderate expansionary investment will promote GDP recovery, but are not conducive to optimizing industrial structure [5].

In addition to the negative impact on various sectors of the macroeconomy, Zhang Xiaoyuan et al. (2022) construct nighttime lighting indicators and argue through spatial autocorrelation analysis that the epidemic has a greater impact on industrial cities, while cities with a predominantly tertiary sector can achieve a rapid recovery [6]. Liu Shuai (2021) highlights the problem of increased regional imbalance and wider disparities between regions brought about by the epidemic [7].

2.2. The Omicron epidemic's impact on unemployment

The literature that empirically explores the impact of the epidemic on employment, although few, has demonstrated that the negative employment shock of the epidemic is significant. Using a dynamic stochastic general equilibrium model, Liu Jindong et al. (2022) analyzed the heterogeneity of firms of different sizes from a microscopic perspective and found that employed SMEs and youth groups received larger employment shocks than large firms [8]. Shen Guobing et al. (2021) also quantified the impact of the epidemic on employment in China from an empirical perspective and sorted out the mechanism, finding that the Omicron epidemic had a significant impact on the unemployment rate in China, and the impact on large cities was smaller than the overall level, and argued that the epidemic had a significant impact on employment levels in China by affecting manufacturing and service industries [9].

Some scholars also analyze from the perspective of labor force segmentation. For example, from the perspective of college graduates, Yue Changjun and Qiu Wenqi (2022), based on sample survey data, found that employment implementation (unit employment, flexible employment and going abroad) of higher in 2021 declined compared to 2019, while the proportion of domestic further education increased [10]. Yang Shengli and Shao Panpan (2021), on the other hand, use a binary logit model from the perspective of migrant workers to demonstrate the significant impact of the epidemic on migrant workers' unemployment [11].

In other research methods, Gao Jingyan (2022) explored employment in the epidemic era from the perspective of labor relations, arguing that under the epidemic, labor patterns developed toward a diversified perspective and the limitations of the dualistic structure of labor relations were magnified as a result [12].

2.3. Literature Review and Innovation

Through literature combing, this paper finds that (1) most of the literature focuses on the impact of the New Crown epidemic on China's macroeconomy, while employment is less explored. (2) The existing literature that explores the impact of the Omicron epidemic on employment has less combing of the impact mechanisms. (3) Since the March 2022 Omicron epidemic occurred relatively recently, there are fewer articles available that focus on this epidemic.

Accordingly, the innovations of this paper are as follows: (1) Focusing the perspective on the impact of the March 2022 Omicron epidemic on employment in the country in the context of the normalization of the epidemic. (2) To conduct a theoretical mechanism analysis regarding the impact of the epidemic on employment. (3) Heterogeneous grouping of the labor force by age group to explore how the impact of the epidemic on the labor force of different age groups is significantly different.

3. Mechanism analysis and hypothesis

3.1. Mechanism analysis

Macroeconomics classifies unemployment (involuntary unemployment) according to the causes of its generation into four categories: frictional unemployment, structural unemployment, seasonal unemployment, and cyclical unemployment. The negative impact of the Omicron epidemic on the job market is mainly caused through frictional unemployment causes and structural unemployment causes, which in turn lead to an imbalance between labor supply and demand.

3.1.1. Frictional unemployment

Macroeconomics, defines the phenomenon of unemployment due to technical reasons as frictional unemployment, which has the characteristics of affecting a wide range of industries and involving many people, but in terms of the time dimension, the impact time depends on the frictional time, so it is a short-term impact.

The Omicron epidemic has had a huge impact on our economy, with a downward economic spiral, reduced corporate income, weakened hiring demand, weakened employment absorption capacity, and further disproportionate resource allocation in the economy in the process of adjustment, with job seekers unable to find suitable positions according to their intentions and the cost of employers seeking to find talent with specific skill sets greatly increased. On the other hand, in addition to the ongoing impact of the Omicron epidemic, China is also facing the employment pressure of the graduation season. The combination of multiple factors has amplified the imbalance between labor supply and demand, further contributing to the rise in unemployment rate.

3.1.2. Structural unemployment

In addition to frictional unemployment, epidemics can also drive structural unemployment. According to macroeconomics, each change in economic industry requires the labor supply to adapt quickly to the change, but the structural characteristics of the labor market do not match the social demand for labor, and the resulting unemployment is called "structural unemployment". By its nature, this effect is long-term.

The economic downward phenomenon brought by the impact of the epidemic has forced the economic structure and industrial structure of China to accelerate the adjustment to adapt to the status quo of the new normal of the epidemic. At the same time, the quality, skills, knowledge reserve and geographical distribution of the existing labor force are sticky and cannot adapt to the accelerated changes of economic restructuring in time. In other words, the demand side of labor is escalating or shifting its demand too fast, and the new demand leads to insufficient new effective supply while the old labor supply is too much. Thus it will intensify further contradiction between supply and demand in the labor market, which will contribute to the rise of unemployment rate.

3.2. Hypothesis Proposal

Based on the above analysis of the current situation and mechanism, it can be tentatively concluded that the Omicron epidemic has a large impact effect on employment in China, according to which, hypothesis 1 is proposed in this paper.

Hypothesis 1:The Omicron epidemic in March 2022 hits our job market and raises our unemployment rate.

The epidemic, which hit the economic development and people's social life in big cities such as Shanghai, especially the 2-month-long home quarantine measure in Shanghai, has seriously affected the economic development in the short term. In addition, the strong employment absorption capacity of big cities has affected the employment of many potential laborers under the impact of the epidemic. Therefore, this paper proposes hypothesis 2.

Hypothesis 2: The March 2022 Omicron epidemic will have a higher employment impact on our major cities and a higher degree of impact on the rise in unemployment.

Compared to the working population with work experience, recent graduates have fewer professional skills and work experience, are less resilient in coping with the employment shock of the epidemic, and therefore will face a greater likelihood of unemployment. Under this scenario, Hypothesis 3 is proposed in this paper.

Hypothesis 3: The March 2022 Omicron epidemic will have a higher employment impact on our recent graduates and a greater impact on the working population aged 16 to 24.

4. Model construction and data sources

4.1. Empirical model construction

This paper adopts the DID method to conduct an empirical analysis on the impact caused by the shock of the current Omicron epidemic on employment in the broader context of the new crown epidemic, with a view to exploring the impact of the Omicron epidemic on employment in China from a quantitative perspective. The reasons for adopting the DID model are as follows: (1) The DID model is currently the mainstream tool for measuring the effects of shocks such as policies. (2) The DID model overcomes the effects of model endogeneity to a great extent. (3) The outbreak of the Omicron epidemic is exogenous to the model and fits the DID assumption.

Accordingly, this paper refers to Shen (2021) to set up the model, and the samples are the relevant monthly data in June 2020 and May 2022. The model setup is specified as follows [14]:

$$UER_t = \beta_0 + \beta_1 TREAT_t * POST_t + \boldsymbol{\beta C}_t + \lambda_t + \varepsilon_t \tag{1}$$

In the model, t denotes month; UER denotes national urban survey unemployment rate; $TREAT_t * POST_t$ is the interaction term of dummy variables and time dummy variables in the experimental group. $\boldsymbol{C}_t$ is the ensemble of control variables, including foreign trade volume and

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foreign direct investment volume. λ_t and ε_t denote time effect and random error effect, respectively. The variables will be elaborated in the next section.

4.2. Variable interpretation and data sources

Dependent variable: national urban survey unemployment rate (UER). The national survey unemployment rate, the surveyed population is the urban resident population (household registration is not required, and the criterion of permanent residence is a full six-month period of residence), is accounted for as the ratio of the number of unemployed people in the surveyed population to the total number of surveyed people and is aggregated to the national level by deduction from this sample data. In addition, this paper also introduces 31 urban survey unemployment rates of major cities to replace the national urban survey unemployment rate, which can explore the impact of the Omicron epidemic shock on major cities on the one hand and serve as a robustness check on the other. Data source from National Bureau of Statistics of China.

Independent variable: omicron epidemic shock ($TREAT * POST$). The core independent variable of this paper, Omicron epidemic shock, consists of the interaction product of the experimental group dummy variable ($TREAT$) and the time dummy variable ($POST$). $TREAT$ portrays the difference between the experimental group and the control group, and this paper refers to the DID selection criteria of cross-sectional data by Fu and Gu (2017), and the period containing the months affected by the current Omicron epidemic, June 2021 to May 2022 as the experimental group, and the data of the previous year corresponding to the experimental group as the control group for comparison and observation [14]. If the sample is in the experimental group, $TREAT$ =1, and if the sample is in the control group, $TREAT$ =0. For the time dummy variable $POST$, the State Council Joint Prevention and Control Mechanism held a press conference at 15:00 on March 19 to inform: "From March 1 to 18, the cumulative number of reported infections in our local epidemic exceeded 29,000 cases. " , because this paper takes March as the dummy variable dividing time for this Omicron epidemic, March, April, and May are assigned a value of 1, and the other months are assigned a value of 0. Therefore, the multiplicative difference $TREAT * POST$ portrays the impact of the Omicron epidemic since March 2022.

Table 1 Model variables and data sources

Variable Type	Variable Name	Variable Symbols	Meaning	Data source
Dependent variable	National urban survey unemployment rate	UER	Urban unemployed population as a percentage of the sum of employed and unemployed population	National Bureau of Statistics
Independent variable	Omicron impact	$TREAT * POST$	The product of the experimental group dummy variable and the time dummy variable	—
Control variables	Total trade	lnTRADE	Natural logarithm of the sum of imports and exports	National Bureau of Statistics
	Foreign Direct Investment	lnFDI	Natural logarithmic value of FDI	Ministry of Commerce of China

Control variables: total trade ($lnTRADE$), foreign direct investment ($lnFDI$). The import/export sector and foreign direct investment are important macro-level variables that affect employment. The total trade variable is first taken as the sum of imports and exports, and then it is subjected to natural logarithm processing, and the data are obtained from the National Bureau of Statistics. For the foreign direct investment variable, the data of foreign direct investment flow in the current month is taken and its natural logarithm is taken, and the data is obtained from the Ministry of Commerce of China.

For descriptive statistics of each variable, see Table 2.

Table 2 Descriptive statistics of variables

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
UER	24	5.338	0.329	4.900	6.100
$TREAT * POST$	24	0.125	0.338	0.000	1.000
$TREAT$	24	0.500	0.511	0.000	1.000
$POST$	24	0.250	0.442	0.000	1.000
$lnTRADE$	24	23.394	0.215	22.926	23.815
$lnFDI$	24	26.893	0.129	26.642	27.098

5. Empirical Results and Analysis

5.1. Parallel trend test

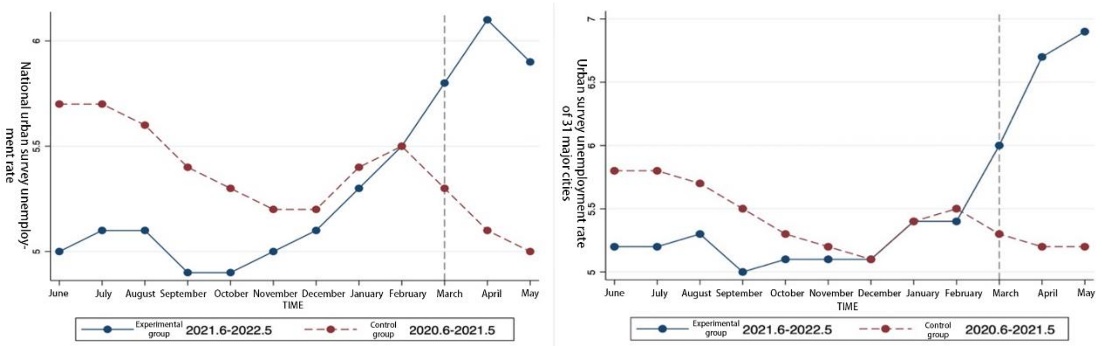

Fig. 1 Impact of the Omicron epidemic shock on the surveyed unemployment rate (vs. previous year)

Figure 1 shows the impact of the March 2022 Omicron epidemic on the national urban survey unemployment rate (left panel) and the urban survey unemployment rate of 31 large cities (right panel), respectively, from a year-on-year perspective. In the left panel, it can be seen that the survey unemployment rate exhibits distinct trends before and after the outbreak: before March, the experimental and control groups show similar trends; after March, the survey unemployment rate in the experimental group shows a rapid upward trend, in contrast to the downward trend in the control group stemming from the rebound of the seasonal unemployment effect. This reflects that the Omicron epidemic had a large impact on the national urban survey unemployment rate in March.

At the same time, the line graph on the right, which takes the urban survey unemployment rate in 31 large cities, reflects a similar trend. From the absolute value level of the y-axis, it can be seen that the Omicron epidemic has a higher degree of negative impact on the unemployment rate in the 31 large cities than the national level.

Figure 1 on the one hand, reflects the significant impact of the Omicron epidemic on unemployment, and on the other hand, it passes the test of the premise parallel trend hypothesis of the DID model.

5.2. Benchmark regression

On the basis of passing the parallel trend test, this paper estimated an empirical model of the impact of the Omicron epidemic shock on the national urban survey unemployment rate, and the results of the benchmark regression are shown in Table 3.

Table 3 Benchmark regression results

	(1)	(2)	(3)	(4)
$TREAT * POST$	0.681*** (0.149)	0.804*** (0.100)	0.800*** (0.228)	0.906*** (0.126)
$lnTRADE$		-1.460*** (0.257)		-1.877*** (0.385)
$lnFDI$		-0.050 (0.155)		0.265 (0.398)
_cons	5.252*** (0.053)	45.686*** (7.422)	5.237*** (0.063)	49.506*** (9.472)
Time fixed effects	No	No	Yes	Yes
Observations	24	24	24	24
adj-R2	0.46	0.78	0.28	0.79

Note: Robust standard errors in parentheses, ***, **, * represent significant at 1%, 5% and 10% significance levels, respectively.

In Table 3, model (1) and model (2) are estimated without fixed time effects, model (3) and model (4) are estimated by introducing time fixed effects, model (1) and model (3) are estimated without considering control variables, while model (2) and model (4) are estimated by introducing control variables on top of model (1) and model (3), respectively.

As can be seen from the results of the benchmark regression, from the perspective of the explanatory variables, the DID variable of the effect of the Omicron epidemic shock on the national urban survey unemployment rate is tested for significance at the 1% level with positive coefficients in all four models with no control variables, with control variables, unfixed time effects and fixed time effects. This indicates that the current round of the Omicron epidemic had a positive effect on the rise in unemployment rate, which means that the effect of the Omicron epidemic on the climb in unemployment rate was significant, more manufacturing and service sector jobs functions that could not be telecommuted during the epidemic were inhibited, and enterprises with insufficient profitability were unable to bear the heavy burden of the epidemic impact and either closed down or dismissed their employees, thus causing an increase in the national urban survey unemployment rate. From the perspective of control variables, only international trade shows a significant effect, the coefficient of international trade sector is negative and passes the significance test at 1% level, indicating that there is an inverse relationship between international trade volume and unemployment rate, the import and export trade sector absorbs more employment volume, under the epidemic, international trade shrinks and the import and export trade volume plummets, making the unemployment rate rise.

Accordingly, the Omicron epidemic causes a significant increase in the unemployment rate and hypothesis 1 holds.

Table 4 then explores how the impact of the Omicron epidemic on the unemployment rate compares to the results of the national urban survey unemployment rate from the perspective of the urban survey unemployment rate in 31 major cities.

Table 4 Benchmark regression results with replacement of independent variables

	(1)	(2)	(3)	(4)
$TREAT * POST$	1.210*** (0.161)	1.349*** (0.133)	1.300*** (0.230)	1.396*** (0.195)
$lnTRADE$		-1.121*** (0.342)		-1.327** (0.596)
$lnFDI$		-0.364* (0.207)		-0.059 (0.617)
_cons	5.324*** (0.057)	43.957*** (9.881)	5.313*** (0.064)	42.364** (9.472)
Time fixed effects	No	No	Yes	Yes
Observations	24	24	24	24
adj-R2	0.71	0.81	0.66	0.77

Note: Robust standard errors in parentheses, ***, **, * represent significant at 1%, 5% and 10% significance levels, respectively.

Comparing Table 4 and Table 3 (model (1) to model (4) set as above), it can be seen that the coefficients of the impact of the Omicron epidemic shock are higher than the results of the benchmark regression under the urban survey unemployment rate sample of 31 large cities, all passing the significance test at the 1% level. The impact of the Omicron epidemic is higher in large cities, exceeding the national average. The reason for this is that since March, there have been outbreaks in mega-cities such as Shenzhen, Shanghai and Guangzhou, with Shanghai bearing the brunt of the outbreak, which has been affected for the longest time and to the greatest depth. Large cities, with more convenient transportation and a larger population base, are more likely to become petri dishes for the virus and accelerate the spread of the epidemic, which means that the risk and resilience of the epidemic will be higher in large cities, which can also accommodate more jobs. Therefore, the extent of the impact of the epidemic on unemployment will be higher in large cities compared to the national average, and hypothesis 2 is tested.

5.3. Dynamic Analysis

Based on the above benchmark regression, this paper refers to Beck et al. (2010) to develop a DID dynamic analysis model to explore the dynamic impact of the Omicron outbreak on the employment situation in China. Taking the month before the outbreak of the Omicron epidemic as the benchmark, the dynamic model is set as follows [15]:

$$UER_t = \theta_0 + \sum_{j=10}^{3} \eta_{-j} \, TREAT_t * POST_t^{-j} + \sum_{j=10}^{2} \eta_j \, TREAT_t * POST_t^{j} + \lambda_t + \varepsilon_t \tag{2}$$

In the model, t denotes the month, if the month difference between each month and March is negative -j, then $POST_t^{-j}$=1, otherwise 0; if the month difference between March and March is positive j, then $POST_t^{j}$=1, otherwise 0. λ_t and ε_t denote the time effect and random error effect, respectively.

In Figure 2, both the left and right panels observe that in the first two months of the Omicron epidemic, the 95% interval of the impact coefficient crosses the straight line of y=0, and the impact coefficient starts to increase gradually in March and after. the essence of the DID dynamic effects analysis is the event study method, so the results in Figure 5 also reflect the parallel trend of the DID model in this paper. The phenomenon of increasing coefficients from March to May indicates that the Omicron epidemic had a significant impact on the urban survey unemployment rate in China, and the experimental group produced a larger increase in the unemployment rate compared to the control group in both the left and right panels. The impact of the epidemic on March and April is higher, and after May, thanks to the government's vigorous "employment stabilization policy", the impact of the Omicron epidemic on employment starts to converge and tends to decrease for the national level, but still has a significant impact compared to the control group; for the 31 large cities, although the impact coefficient maintains the trend of increasing, but the growth rate slows down significantly, which also reflects to some extent that the policy reaps positive feedback.

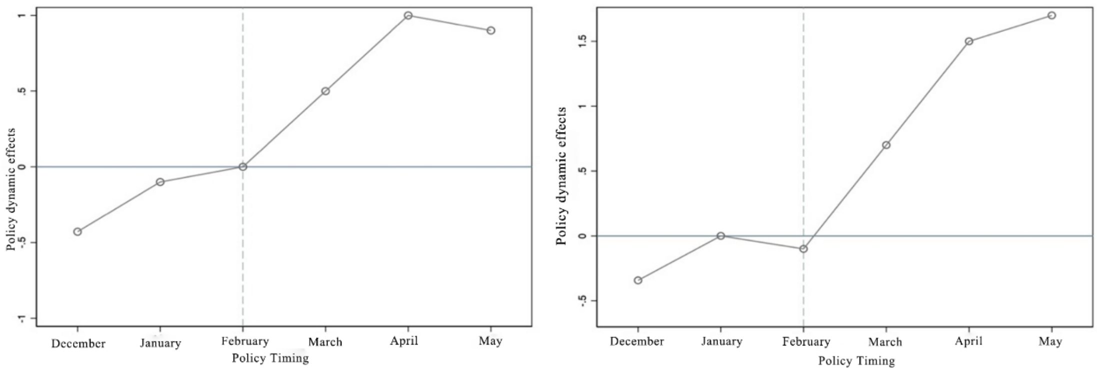

Fig.2 Graph of the dynamic effect of the Omicron epidemic on China's employment impact (left: national urban survey unemployment rate; right: urban survey unemployment rate of 31 major cities)

The dynamic model analysis leads to the conclusion that the Omicron epidemic contributed to the increase in unemployment and to a deeper extent in large cities, i.e., it further supports the conclusions of hypothesis 1 and hypothesis 2.

5.4. Robustness tests

In this paper, a placebo test is adopted as a robustness test of the DID model. This is done by shifting the occurrence of the Omicron epidemic forward in time, setting a new policy occurrence month in place of the true policy occurrence month, and conducting 500 random sample regressions with the estimated coefficients of random assignment shown in Figure 3.

It can be seen that the means of the estimated coefficients of the shocks of the explanatory variable of this paper, the Omicron New Crown epidemic, approximately obey a normal distribution and lie in the vicinity of the zero value, as expected from the placebo test. In addition, the distribution of the coefficients in the right panel is broader compared to the left panel. This indicates that hypothesis 1 and hypothesis 2 in the previous section pass the robustness test of the placebo test.

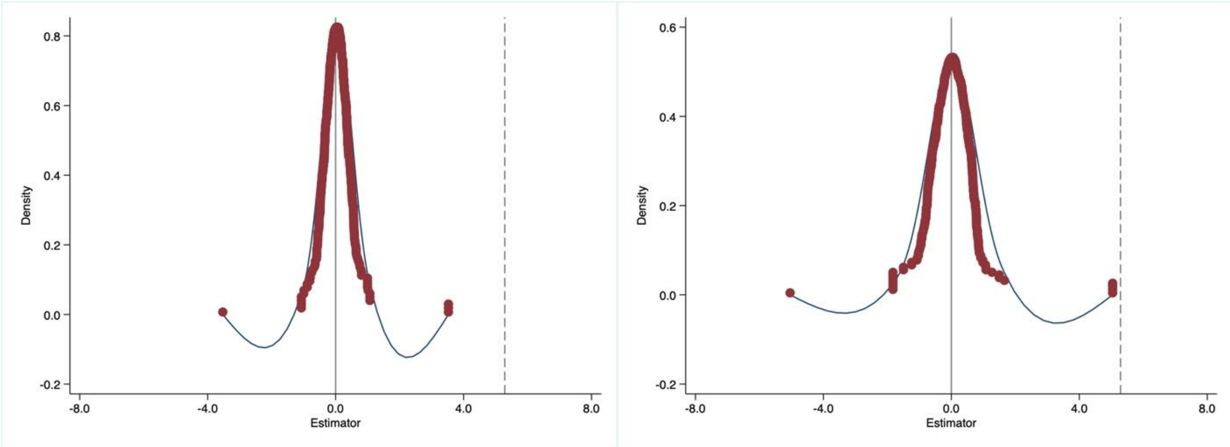

Fig.3 Placebo test (left: national urban survey unemployment rate; right: urban survey unemployment rate of 31 major cities)

Note: The x-axis represents the estimated coefficients from 500 randomly assigned *TREAT*POST*. The curve is the estimated kernel density distribution and the dots are the associated p-values. The vertical dashed line indicates the results of column (4) of the two benchmark regressions.

6. Further Analysis

Based on the previous section, we can basically confirm the negative impact of the Omicron epidemic on China's job market. In the next section, we will analyze the heterogeneity of the impact of the Omicron epidemic on the urban survey unemployment rate for different age groups. Specifically, the model in this section is set up with reference to model (1), replacing the explanatory variables with "national urban survey unemployment rate for the population aged 16-24" and "national urban survey unemployment rate for the population aged 25-59", so as to explore the impact on the labor force of different age groups. The effect on the employment situation of different age groups is investigated.

Table 5 reflects the heterogeneous regression results, with models (1) and (2) focusing on the impact of the Omicron epidemic on the urban survey unemployment rate of the population aged 16 to 24 years, and models (3) and (4) focusing on the performance of the 25 to 59 age group, in addition to models (2) and (4) introducing relevant control variables based on models (1) and (2). The regression results are all fixed for time effects.

The independent variables of the model pass the significance test at the 1% level with positive sign under all four empirical models, and in terms of coefficients, the coefficients of (1) and (2) are much higher than those of the corresponding (3) and (4). This indicates that the Omicron epidemic contributes to a situation of increased unemployment in the 16 to 24 age group and the 25 to 59 age group, and the degree of impact is much higher for the 16 to 24 age group than for the 25 to 59 age group. Analyzing the reasons, the labor force of 16 to 24 years old includes many fresh graduates, and it is the graduation season in June, and the size of 2022 graduates reaches 10.76 million, which is another record high. Under the catalytic effect of the Omicron epidemic, the frictional unemployment and structural unemployment factors will further contribute to the rise of unemployment rate in this age group. In addition, the younger labor force lacks both vocational skills and breadth and depth of work experience compared to the older labor force, which also contributes to the younger labor force being more likely to fall into the unemployment spiral. Thus, hypothesis 3 is empirically verified.

Table 5 Heterogeneity regression results

	Age: 16~24		Age: 25~59	
	(1)	(2)	(3)	(4)
$TREAT * POST$	3.867*** (0.868)	3.485*** (0.829)	0.600*** (0.304)	0.774*** (0.118)
$lnTRADE$		0.343 (2.538)		-2.506*** (0.362)
$lnFDI$		4.099 (2.628)		-0.016 (0.375)
_cons	14.375*** (0.243)	-90.673 (62.456)	4.613***(0.085)	72.366*** (8.909)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	24	24	24	24
adj-R2	0.58	0.64	0.79	0.84

Note: Robust standard errors in parentheses, ***, **, * represent significant at 1%, 5% and 10% significance levels, respectively.

7. Conclusions and Policy Recommendations

7.1. Conclusion

This paper explores the impact of the Omicron epidemic on the employment situation in the country from a quantitative perspective, using monthly data from June 2020 to May 2022, and the following conclusions are drawn:

(1) The Omicron epidemic will exacerbate the imbalance between supply and demand in China's job market by acting as a catalyst for "frictional unemployment" and "structural unemployment", which will have a significant negative impact on China's employment situation. In terms of dynamic effects, the country's successive employment stabilization policies have, to a certain extent, restrained the rate of increase in unemployment in May.

(2) Because omicron is more contagious, the likelihood of recurrence is higher in large cities, and large cities have a higher capacity to absorb employment, the home quarantine measures brought about by the outbreak contribute to higher unemployment. That is, Omicron has a greater impact on large cities.

(3) The younger labor force group will show a significant lack of resilience when fighting employment shocks from the epidemic due to their inadequate job skills, work experience, and exposure to an increasingly intense employment environment. As a result, the Omicron epidemic has had a greater degree of employment shock on the younger workforce.

7.2. Policy Recommendations

For the government: First of all, the government should assess the risk of epidemic in advance as well as formulate corresponding countermeasure policies in time to reduce the cost and free cost of epidemic prevention to the society. The prerequisite for insisting on dynamic clearance and precise epidemic prevention is science and accuracy, and strictly preventing internal laziness and negligence, moreover, avoiding one-size-fits-all policies. Restore social functions and ensure the normal flow of all factors in order to play the regulatory role of the market and realize the effective allocation of labor resources. Secondly, the government needs to correctly and scientifically measure the effect of the employment stabilization policies implemented, so as to make precise efforts. For college graduates, the government should promote enterprises to expand the scale of employment, broaden the employment space at the grassroots level, and also optimize supporting measures to support self-employment. For the unemployed and difficult groups, while implementing the employment subsidy policy, it is also necessary to strengthen skills training. Finally, the government should also actively promote the use of electronic information platforms to reduce the information gap between labor supply and demand and reduce the impact of frictional unemployment. In addition, it is more important to prohibit employment discrimination against positive rehabilitated patients by various business units.

For the labor force: First, it is important to understand the situation and find the right positioning. Under the situation of increasing unemployment rate of the epidemic, complex changes in the job market and repeated risks of the epidemic, adapt to the changes in the economy, pay attention to the changes in the market jobs, adjust expectations in time, find employment first before choosing a career, and find your own positioning in practice. Most importantly, improve your professional skills and career quality, get out of your comfort zone, increase your human capital through knowledge learning and vocational training, and improve the match with your career, so as to improve your competitiveness in job hunting and mitigate the long-term impact of structural unemployment.

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