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ARTICLE

Research on Influences of Employment in Manufacturing Industry on that in the Service Industry Based on Bayes Model

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ABSTRACT

Using the data of 285 prefectural and the above-level cities from 2004 to 2016, this thesis reveals the impact of employment in China's urban manufacturing industry on the employment of service industries with the Bayesian model. Under the Bayesian framework, partial linear semi-parametric model is proposed. The nonlinear functions are fitted by using truncation base cardinal spline and considering the random error terms of mixed normal fitting models. The results show that: employment in the urban manufacturing industry in China has significant influence on the employment in the service industry. When the number of employees in the manufacturing industry changes from 0 to 650,000, the manufacturing industry has less influence. When the number of the employees in the manufacturing industry changes from 650,000 to 900,000, the employees of the service industry will dramatically increase. When the number of the employees in the manufacturing industry is more than 900,000, the employees in the service industry will be prone to stable growth.

1. Introduction

From 21th century, a large proportion of new employment posts of most developed countries in the world originated from the service industry. At the same time, China pays much attention to growth of large-scale employment posts in the manufacturing industry and further optimizes the employment structure, so different employees transfer from the low-efficiency production departments to the moderate and highly efficient production department. Research on new employment posts in China is very meaningful in theory and practice to improve urbanization speed and level in China, optimize the economy structure and industry structure and improve the employment rate.

Domestic scholars have conducted plentiful theoretical research and discussion on the employment effect in the manufacturing industry and service industry. Yifei Li, Jing Li and Ming Xu (2017) established a measurement model and the results of the model show a causal relationship between employment in the manufacturing industry and

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the service industry. Every 1% increase of employment in the urban manufacturing industry will lead to employment growth of 0.47% in the manufacturing industry. On the contrary, every 1% increase of employment in the service industry will boost 1.5% of employment growth in the manufacturing industry.[6] Desheng Lai and Man Gao (2017) studied multiplier utility of employment in the manufacturing industry and service industry by using the tool variant method. The results show that the multiplier utility varies in the eastern, central and western China. The employment multiplier utility of the labor market with different scales is very different. The larger the labor market is, the higher the multiplier utility of the manufacturing industry on the service industry would be.[7] Yu Li (2016) conducted empirical analysis by using the measurement model and tool variant. The results show that the employment effect of the high-end manufacturing industry is higher than that of the middle and low-end manufacturing industry, and the bigger a city is, the more obvious the employment multiplier effect of the manufacturing industry will become.[8]

Based on the above analysis, although there are analysis and research in existing references, Bayes model has yet to be used to study influences of the manufacturing industry on the service industry in China. In a word, a partially linear model is established under the Bayes frame to make the results approximate to true distribution due to weaknesses in the existing references. The mixed normal fitting errors are used to study the influence of urban employment in China on employment in the local service industry and differences of employment effect in city scales and regional differences of employment effect in the manufacturing industry are further investigated in this paper.

2. Model Construction

This paper recommends the semi-parametric partially linear model as follows:

$$y_i=x_i^T\alpha+f(t_i)+\epsilon_i \tag{1}$$

$\alpha=(\alpha_1...\alpha_p)^T$ is the linear unknown parameter vector, $x_i=(x_{i1}...x_{ip})^T$ is the covariant vector of i_{th} individual and y_i is the dependent variable. The unknown parameters $f(t)$ exists and it is not practicable to estimate the unknown parameter by using Bayes, so the following splines under the Bayes frame is used to approximate to the unknown smooth function $f(t_i)$,

$$f(t_i)=\beta_0+\beta_1 t_i+...+\beta_s t_i^s+\sum_{l=1}^{I}\beta_{s+l}(t_i-K_l)_+^s=Z^T(t_i)\beta \tag{2}$$

The s is multinomial order (freedom of the spline), I is the node number defined for approximate smooth function, the node I is equivalent to $I+1$ regression intervals defined for the smooth function. For easy description, given that the regression coefficient vector $\beta=(\beta_0, \beta_1..., \beta_s, \beta_{(s+1)}, \beta_{(s+I)})^T$ and the spline's basic vector $Z(t_i)=(1, t_i, ... ,t_i^s, (t_i-K_l)_+^s,...,(t_i-K_I)_+^s)^T$, here the truncation power base function $a_+^s=\{\max(a,0)\}^s$, K_l is l_{th} node. Generally the node number d is between 20-40 < so it can ensure enough flexibility.

It's generally supposed in the typical partial linear model that the measurement error vector ϵ_i of the response variants is subjective to parameter distribution such as normal distribution. When the actual distribution is different from the given normal distribution, it may lead to incorrect conclusions. Therefore, to enhance the model flexibility, capture more data information and ensure model robustness, the error ϵ_i of the response variants are subjective to the mixed normal distribution in the model (2).

$$\epsilon_i\sim\sum_{g=1}^{G}\pi_g N(\mu_g, \sigma_g^2), \tag{3}$$

Here π_g is a random weight and indicates the probability of getting g^{th} *normal* distribution. Its value ranges from 0 to 1 and satisfies $\sum_{g=1}^{G}\pi_g=1$. G is the set positive integer and indicates the number of optional normal distributions for ϵ_i distribution approximation. Generally satisfactory results can be obtained when G is between 20 50.[6] However, it is difficult to conduct Bayes deduction from the mixed normal distribution above. Generally the latent variant L_i is used to record ϵ_i distribution. ϵ_i is subjective to normal distribution under the given L_i condition.

$$\epsilon_i\,|\mu, \sigma, L_i\sim N(\mu_{Li}, \sigma_{Li}^2), \tag{4}$$

σ_{Li}^2 is L_i^{th} vector in the variance set σ^2 and $\sigma^2=\{\sigma_g^2: g=1,..,G\}$. Given that the prior distribution is $(\sigma_g^2)^{-1}\sim$Gamma(c_1,c_2).

Similarly, μ_{Li} is the L_i mean vector in the mean vector set $\mu=\{\mu_g: g=1,...G\}$. Suppose the prior distribution is $\mu_g\sim(\mu_\mu, \sigma_g^2)$, generally μ_μ gives a normal prior distribution and L_i can be generated from the following multi-point distribution:

$$L_i\,|\pi\sim\text{Multinomial}(\pi_1, ..., \pi_g), \tag{5}$$

Here $k_g\sim Beta(1,\tau)$, $g=1$, ... G and $k_G=1$ is regulated to make $\sum_{g=1}^{G}\pi_g=1$.

For the convenience of calculation, the equation (2) is substituted into the equation (1) to get the fully linear equation (1):

$$y_i=w^T\gamma+\epsilon_i, \tag{7}$$

$w_i=(x_i^T, z_i^T)^T$ and $\gamma=(\alpha^T, \beta^T)^T$. Given that $\theta=\{\gamma, \theta_\epsilon\}$,$\theta_\epsilon$ indicates unknown parameters on error ϵ_i and $y=\{y_i \mid i=1, ..., n\}$. The prior distribution of the unknown parameters in the model (7) are set as follows: $\pi(\alpha)\sim N_p(\alpha_0, \sigma_\alpha^2 I_p)$ and $\pi(\beta)\sim N_{s+I+1}(\beta_0, \sigma_\beta^2 I_p)$. After two equations are combined, $\pi(\gamma)\sim N_{p+s+I+1}(\gamma_0, \Sigma_r)$. $\gamma_0=(\alpha_0^T, \beta_0^T)^T$, $\Sigma_r=\begin{bmatrix}\sigma_\alpha^2 I_p & 0\\ 0 & \sigma_\beta^2 I_p\end{bmatrix}$ and σ_α^2 and σ_β^2 are the super parameters. Bigger the value is, smaller the prior distribution is. On the contrary, if the value is smaller, it indicates more information on unknown parameters. The α_0 and β_0 values are estimated by using other methods. If no other methods are available, generally it takes 0.

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3. Empirical Analysis

3.1 Introduction to Data Estimation Method

Based on the theory above, a model can be used to analyze the relation between the manufacturing industry and service industry via the relation equation (1).

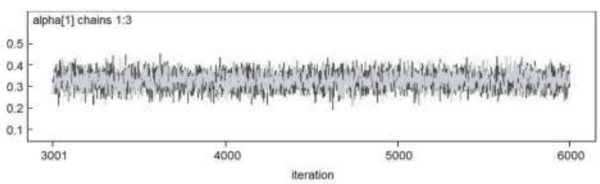
Given that the prior distribution of the super parameter α is a normal distribution. First we conduct linear regression by using the least square method to get the parameter and use it as the initial value of the super parameter α in the Markov chain.[4,5]We set the initial value α=(0.037,0.336,0.283). The prior distribution of all parameters from α_1 to α_3 is set as N(0,1).y_i is the number of the practitioners in the service industry of different cities.[2,3] The spline t_i is set as the number of practitioners in the manufacturing industry of cities, $f(t_i)$ is the spline, namely non-linear part. The equation (2) is used to linearize $f(t_i)$. The number of nodes in this equation is selected as 20 and the corresponding unknown parameters are from β_1 to β_{23}. The prior distribution is given as follows.The prior distribution of β_k is N(0,10), k=1,2,3,4. The prior distribution of β_{k+q} is $N\beta(_{k+q-1},\tau)$ and q=1,...,19, τ~Gamma(0.1,0.1); ϵ_i error is fitted by the mixed normal distribution. For the linear part $x_i^T\alpha$, x_i^T is the 3D data. We set x_1 as the area of the urban construction land, x_2 is set as the gross output of the city. To avoid disturbance in different years, we set x_3 as the year. 1 is recorded for 2004, 2 is recorded for 2005 and 3 is recorded for 2006. Others are deduced similarly. x_4 is added to represent regional difference and urban scale difference and further analyze influences of these differences.

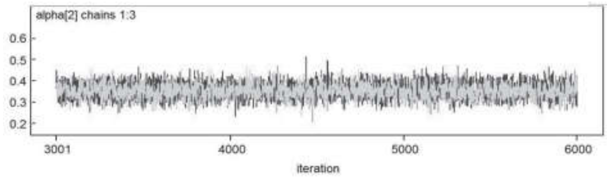
3.2 Data Source and Processing

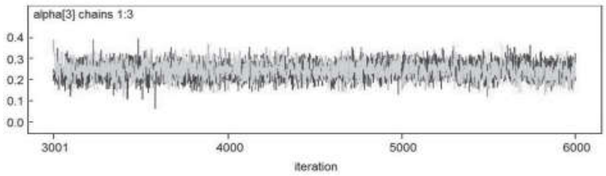
The data from different provinces and cities, municipalities and autonomous regions are selected are selected as the sample points based on data in 2004-2016 Statistics Yearbook for cities in China. The data are processed as follows for all areas. To maintain data confidence level and uniformity of data, the data are pre-processed. Cities without complete years and sample points without significant differences are removed. To eliminate influences due to the unit, the data is standardized.

3.3 Empirical Results and Related Analysis

The above data are iterated by calling the WINBUGS software in the R package for 6000 iterations. [1]







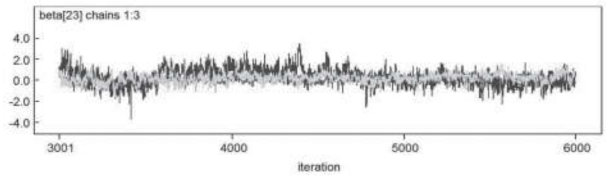


Figure 1. Iteration effect

The Figure 1 shows that three Markov chains are nearly overlapped, so the Markov chain converges roughly and reaches the stable status. This model features better fitting effect.

The results in the Table 1 show that the standard deviation SD and MC error (standard deviation of posterior sample means) are very small and can be ignored nearly, so the results are relatively reliable.

Table 1. Posterior results of parameters

Parameter	Mean	Standard deviation	MC error
α1	0.036	0.005	0.000
α2	0.335	0.068	0.005
α3	0.283	0.010	0.000
β1	8.734	12.140	0.878
β2	-0.090	0.124	0.010
β3	0.420	0.274	0.021
β4	0.347	0.633	0.050
β5	0.090	0.236	0.018
β6	-0.177	0.500	0.039
β7	-0.072	0.190	0.015
β8	-0.038	0.248	0.019
β9	-0.162	0.369	0.029
β10	-0.011	0.434	0.034
β11	-0.035	0.275	0.021
β12	-0.048	0.284	0.022
β13	-0.021	0.333	0.026
β14	0.271	0.702	0.055
β15	0.089	0.390	0.030
β16	0.107	0.130	0.010

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β17	-0.210	0.449	0.035
β18	-0.162	0.657	0.051
β19	-0.391	1.171	0.092
β20	0.058	0.654	0.051
β21	0.187	0.397	0.030
β22	0.210	0.313	0.021
β23	0.204	0.430	0.028

Figure 2. Fitting diagram of the influence of manufacturing industry on employment in the service industry

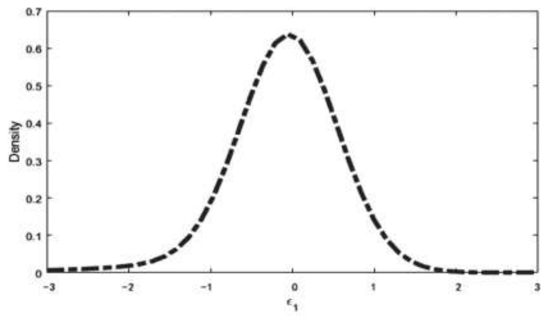

Figure 3. Kernel density distribution

We draw the splines, as shown in the figure 2. Based on the curve, when the number of employees in the manufacturing industry changes from 0 to 650,000, the manufacturing industry has less influence on the number of employment in the service industry and employees of the service industry may increase or decrease. When the number of the employees in the manufacturing industry changes from 650,000 to 900,000, the employees of the service industry will dramatically increase. At this time, the manufacturing has significant impact on the employees of the service industry and the effect is optimal. It indicates that developed manufacturing industry in the cities can drive employees of the service industry. When the number of the employees in the manufacturing industry is more than 900,000, the employees in the service industry will grow stably because the employment space of the urban service industry is limited and will not increase without a limit with changes of the manufacturing industry. Therefore, when the employees are in a small number in the manufacturing industry, it will have less impact on the employees in the service industry and can also show undeveloped service industry of small cities to some extent. When the employees of the manufacturing industry reach certain scale, the employees in the service industry will increase massively. When the manufacturing industry reaches certain scale, it will have significant influence on the service industry and increase the employees in the service industry. When the number of employees in the manufacturing industry exceeds a limit, it is prone to stable growth, which complies with the decreasing law of the marginal effect in the economy, that is, with the growth of the employees in the manufacturing industry, the effect of employment in the manufacturing industry on that in the service industry will decrease. In addition, the influence of employment in the manufacturing industry on that in the service industry is also restricted by other factors. For instance, growth space of new employment in the service industry of some cities is limited, or support of the policies for the service industry decreases, so the employees in the service industry change less. The kernel density distribution of the figure 3 shows the unimodal normal distribution of errors.[9]

4. Conclusion

Employment in the urban manufacturing industry in China has significant influence on the employment in the service industry. When the number of employees in the manufacturing industry changes from 0 to 650,000, the manufacturing industry has less influence on the employment number of the service industry and employees of the service industry may increase or decrease. When the number of the employees in the manufacturing industry changes from 650,000 to 900,000, the employees of the service industry will dramatically increase. At this time, the manufacturing has significant influence on the employees of the service industry and the effect is optimal. It indicates that the urban agglomeration economy can boost the number of employees of the service industry. When the number of the employees in the manufacturing industry is more than 900,000, the employees in the service industry will be prone to stable growth because the urban agglomeration economy will be offset by the urban congestion effect. The space for employment of the urban service industry is limited and will not increase without a limit along with the changes of the manufacturing industry.

  DOI: https://doi.org/10.26549/jfr.v2i3.1173

References

[1] Albert, J. Bayesian Computation with R (2nd Ed) Springer[M], New York, 2009.

[2] Gelman, A. Prior distributions for variance parameters in hierarchical models[J]. Bayesian Analysis 2006(6):515-533.

[3] Good, I.J. Probability and the Weighing of Evidence[M]. Charles Griffin, London, 1950.

[4] Hastings W K. Monte Carlo sampling methods using Markov chains and their application[J]. Biometrika,1970: 97-109

[5] Ishwaran H, Zarepour M. Markov chain Monte Carlo in approximate Dirichlet and beta two-parameter process hierarchical models[J]. Biometrika, 2000(2),371-390

[6] Ohlssen D I, Sharples L D, Spiegelhalter D J. Flexible random-effects models using Bayesian semi-parametric models: applications to institutional comparisons[J]. Statistics in Medicine, 2007(9):2088-2112.

[7] Desheng Lai, Man Gao. The Creation of Local Employment: Multiplier Effect of Manufacturing Employment on Service Employment[J]. Chinese Journal of Population Science, 2017(04):28-40. (in Chinese)

[8] Yifei Li, Jing Li, Ming Xu. The Interactive Multiplier and Spatial Spillover between Manufacturing Employment and Service Employment[J]. Finance Trade Economics, 2017(04):115-129. (in Chinese)

[9] Yu Li. Employment multiplier effect of manufacturing sector on local service sector: Empirical research based on the provincial panel data[D].2016. (in Chinese)