Team Number :	2020230040158

Problem Chosen :	B

2020 APMCM summary sheet

In order to solve the problem of the impact of the US election results on the Sino-US economy, this paper uses Lagrange interpolation and principal component analysis to complement and reduce the historical data, build a predictive model based on BP neural network, and use the VAR model to analyze the future economy development status, and establish an analytic hierarchy model based on multiple linear regression to evaluate and analyze the results of the general election.

Question 1 requires a quantitative analysis of the impact of the election of different candidates on the US economy. By comparing the similarities and differences between the two candidates' policy propositions, we extract relevant policy indicators to express their impact on the US economy and collect historical data. For missing data, Lagrange interpolation is used to complete the original data. Due to the large number of policy indicators, it is considered to conduct principal component analysis on policy indicators, and to establish a prediction model based on BP neural network, using historical data of principal component indicators to predict various principal component indicators in the next 4 years. Finally, the VAR model is used to calculate the predicted value of economic indicators using the predicted value of the principal component indicators to analyze the future economic development of US.

Question 2 is to analyze the impact on the Chinese economy. Assuming that only the two candidates' China policy will affect China's economy, four China policy indicators are extracted, and the predicted value of China's economic indicators is calculated based on question 1, and the future economic development of China is analyzed.

Question 3 requires combining the mathematical models of Question 1 and Question 2 to propose economic countermeasures that China should take when Trump and Biden are elected. By constructing an analytic hierarchy model based on multiple linear regression, the index weights are obtained according to the hierarchical ranking method. The results show that Biden's election weight is 0.51, and Trump's election weight is 0.49. There is not much difference between the two, indicating that the policies of the two candidates have similar effects on the China's economy. Among the ten policy indicators, the top three weighted indicators are the Stock price general 500 index, the trade deficit and the total import and export volume. These indicators mainly correspond to the financial and trade policies of the United States. In response to these policies, appropriate Chinese economic policies are proposed.

The innovation of this paper is to adjust the prediction results of the BP neural network based on the impact of the epidemic to make it more in line with the actual situation, and use the VAR model to analyze and determine the future economic development status. In the analytic hierarchy process, the multiple linear regression method is used to construct the judgment matrix, which avoids the shortcoming of the subjectiveness of the expert score.

Keywords: Lagrange interpolation, principal component analysis, BP neural network, VAR model, multiple linear regression, AHP

Contents

1 Problem background and restatement

1.1 Problem background

The US presidential election is held every four years. 2020 is the year of the US presidential election. The 59th President of the United States will be elected. Republican candidate Donald Trump and Democratic opponent Joe Biden will participate in the election. The two sides have held three presidential election debates since September 2020. The general election was officially held on November 3. Candidates on both sides have different policies in finance and trade, economic and financial governance, and other key development areas (such as COVID-19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.). Given that the United States has a major impact on world development in many aspects, the election of different candidates will shape different strategic models of global economic and financial development, and have a greater impact on the U.S. economy and the global economy (including the Chinese economy). How will different policies affect the economies of the United States and China? How should China respond?

1.2 Problem restatement

Based on the above background, on the basis of collecting candidates' policy propositions, policy guidelines and related data in different fields, the following questions are answered:

(1)Establish a mathematical model and use relevant data to quantitatively analyze the possible impact of different candidates elected on the U.S. economy. (You can choose one or several fields to answer this question separately or give a comprehensive answer)

(2)Establish a mathematical model and use relevant data to quantitatively analyze the possible impact of different candidates elected on China's economy. (You can choose one or several fields to answer this question separately or give a comprehensive answer)

(3)Suppose you were members of China's Think Tank for Economic Development, combined with the mathematical models of questions 1 and 2, what suggestions would you make to China's economic countermeasures and policies in related areas in both cases (which party wins)? Please illustrate your points specifically.

2 Problem analysis

2.1 Problem one analysis

Problem one requires the establishment of a mathematical model to quantitatively analyze the impact of the election of different candidates on the US economy through relevant data.

First, it is necessary to compare and analyze the similarities and differences between the two candidates' policy proposals, which mainly include COVID-19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.

Secondly, different candidates adopting different policy propositions will result in different economic development conditions. In order to characterize this impact, select corresponding related policy indicators for each policy, including infrastructure investment, tax income, average CO_2 emissions, average domestic general government health expenditure, unemployment rate, total import and export, trade deficit, stock price general 500 index, total international migrants and percentage of education expenditure. On the other hand, in order to quantitatively judge the economic development status, relevant economic indicators such as Gross Domestic Product、Producer Price Index、average Gross National Income are selected. Collect historical data for these indicators.

Thirdly, in view of the large number of policy indicators and the fact that not all information is primary, principal component analysis is performed on these indicators to extract comprehensive indicators reflecting policy changes while reducing dimensions.

Fourthly, in order to predict the principal component indicators, a predictive model needs to be established. In view of the many advantages of BP Neural Network, this paper uses BP Neural Network to establish a prediction model, and uses the historical data to predict the various principal component indicators in the next 4 years.

Finally, predicting economic indicators based solely on historical data cannot reflect the impact of policy changes. In order to calculate the predicted value of economic indicators through the predicted value of the principal component indicators, it is necessary to find the relationship between economic indicators and the principal component. This paper analyzes the relationship based on the VAR model. Then substituting the predicted value of the principal component indicators into the model to obtain the predicted value of economic indicators, and then analyze the economic development status.

2.2 Problem two analysis

Problem two requires the establishment of a mathematical model to quantitatively analyze the impact of different candidates' election on China's economy through relevant data.

Different from problem 1, only two candidates' China policies will affect China's economy in problem 2. Therefore, in problem 2, indicators related to China's policies are selected to characterize the impact of different candidates on China's economy, including China's foreign trade cargo throughput, US imports and exports to China, US dollar to RMB exchange rate and US federal fund interest rate. On the other hand, in order to quantitatively judge the development of China's economy, China's total import and export and customs duties are selected as indicators to measure China's economy. As the first one is similar to other principal component analysis, it is not necessary to extract principal component analysis.

2.3 Problem three analysis

Problem three requires combining the mathematical model of question 1 and question 2 to put forward the economic countermeasures that China should take when Trump and Biden are elected respectively.

In order to analyze the impact of the two candidates on China’s economy after being elected, this paper uses the analytic hierarchy process model based on multiple linear regression to determine the influence weight of each policy and the influence degree of the two candidates on China’s economy. In order to avoid the subjectivity of analytic hierarchy process (AHP), based on the data of first and second questions, the multiple linear regression method is used to determine the judgment matrix. Finally, the influence and countermeasures are analyzed according to the results of hierarchical ranking.

3 Problem hypothesis

(1) It is assumed that the candidate will implement the published policy proposition after taking office.

(2) According to the development of COVID-19 vaccine, it is assumed that the epidemic will not last until the end of the next tenure.

(3) Ignore the impact of non-policy factors on China's and the U.S. economy.

(4) It is assumed that the error of BP Neural Network does not affect the solution of the economic model.

4 Symbol description

For the convenience of reading and understanding, the important variables in this paper are explained in a unified manner, as shown in Tab.1.

Tab.1 Symbol description

Symbol	Description	Symbol	Description
X_1	Infrastructure investment	Z_1	China's foreign trade cargo throughput
X_2	Tax income	Z_2	US imports and exports to China
X_3	Average CO_2 emissions	Z_3	Exchange rate of US dollar to RMB
X_4	Average domestic general government health expenditure	Z_4	US federal funds rate
X_5	Unemployment rate	S_1	Problem one training set1
X_6	US total import and export	S_2	Problem one training set2
X_7	Trade deficit	S_3	Problem two training set1
X_8	Stock price general 500 index	S_4	Problem two training set2
X_9	Total international migrants	T	Problem one testing set
X_{10}	Percentage of education expenditure	U	Problem two testing set

5 Model and solution of problem one

5.1 Comparison of policy propositions

The election candidates Trump and Biden represent the Republican Party and the Democratic Party respectively. The two parties have very different governing ideas. Therefore, the policy propositions of the two candidates during the election process are very different. Policy propositions are important references for predicting the candidate's ruling situation after winning the election. Therefore, it is necessary to compare and display the main policy propositions of the two candidates, including COVID-19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.

Tab.2 Comparison of Different Candidates' Policy Propositions

Policy Propositions	Trump	Biden
COVID-19 fighting measures	Passive: No mandatory epidemic prevention policy; Exit WHO	Active: Every people need wear masks; National Testing; Rejoin WHO
Infrastructure	Invest 1 trillion dollars in the next 10 years	Invest 2 trillion dollars in the next 4 years
Taxation	Comprehensive tax cuts for middle-class families and small businesses	Cancel tax cuts
Environmental protection	Persist in the development of traditional energy, withdraw from the Paris Climate Agreement	Increase clean energy investment, rejoin the Paris Climate Agreement
Medical insurance	Reduce medical costs through market competition and abolish Obamacare policy	Realize affordable medical care through government intervention and implement Obamacare reform
Employment	Promote the achievements during the ruling period such as the return of manufacturing and employment	Emphasis on raising the minimum wage, promoting racial equality and other government safeguards
Trade	Continue to implement the punitive tariffs of "unfair dumping and subsidies" and refuse to join the TPP	Put pressure on other countries through alliances
Immigration	Strengthen border security, repeal Obama's immigration reform executive order, and withdraw from the global immigration convention	Withdraw Trump's immigration policy
Education	Help students in the form of aid	Student loan exemption, expansion of tuition-free universities, universal preschool education, etc.

5.2 Data acquisition and preprocessing

5.2.1 Data acquisition

Question 1 requires a quantitative analysis of the impact of different candidates on the US economy. Obtaining comprehensive and true data is a prerequisite for solving the problem. The data should include two aspects: (1) Policy indicator data that can reflect the impact of policy changes. The data structure is shown in Table 3. It should be noted that since the COVID-19 epidemic is an emergency, the impact of the epidemic and the corresponding epidemic prevention policy cannot be reflected in the historical data, so it will be considered separately in the model; (2) Economic indicator data that characterizes economic changes. It mainly considers three items: Gross Domestic Product (GDP), Producer Price Index (PPI), and average

Gross National Income (A_GNI). The data structure is shown in Table 4. After extensive data collection, the complete data results obtained are shown in Attachment 1. The data source is the World Economic Database of China Economic Information Network.

Tab.3 Policy indicator data structure

Time(quarterly)	X_1 (billion dollars)	X_2 (million dollars)	X_3(mt /person)	X_4 (dollar)	X_5(%)
Time(quarterly)	X_6 (million dollars)	X_7 (million dollars)	X_8	X_9(person)	X_{10}(%)

Tab.4 Economic indicator data structure

Time	GDP（billion dollars）	PPI	A_GNI（dollar）

5.2.2 Data preprocessing

After checking the acquired data, it is found that some indicators only have partial data values. The main purpose of data preprocessing is to make data interpolation. Commonly used interpolation methods include mean/median/mode interpolation, fixed value, nearest neighbor interpolation, regression method and interpolation method, considering that the results of interpolation method are more accurate and only need to use the information of known points, therefore, using Lagrange interpolation method to impute missing values. Data interpolation can not only improve data quality, but also improve the accuracy of fitting and prediction in the model. The basic steps of Lagrange interpolation are as follows:

Step1: For n known points on the plane (no two points are on a straight line), a polynomial of degree $n-1$ can be obtained $y = a_0 + a_1 x + a_2 x^2 + ... + a_{n-1} x^{n-1}$, the curve of the polynomial passes through these n points, and substitute the coordinates of the n points $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$ into the polynomial:

$$\begin{aligned} y_1 &= a_0 + a_1 x_1 + a_2 x_1^{\,2} + ... + a_{n-1} x_1^{\,n-1} \\ y_2 &= a_0 + a_1 x_2 + a_2 x_2^{\,2} + ... + a_{n-1} x_2^{\,n-1} \\ &\vdots \\ y_n &= a_0 + a_1 x_n + a_2 x_n^{\,2} + ... + a_{n-1} x_n^{\,n-1} \end{aligned} \tag{1}$$

Step2: Solve the Lagrange interpolation polynomial:

$$\begin{aligned} L(x) &= y_1 \frac{(x-x_2)(x-x_3)\cdots(x-x_n)}{(x_1-x_2)(x_1-x_3)\cdots(x_1-x_n)} + y_2 \frac{(x-x_1)(x-x_3)\cdots(x-x_n)}{(x_2-x_1)(x_2-x_3)\cdots(x_2-x_n)} \\ &+\cdots+ y_n \frac{(x-x_1)(x-x_2)\cdots(x-x_{n-1})}{(x_n-x_1)(x_n-x_2)\cdots(x_n-x_{n-1})} = \sum_{i=0}^{n} y_i \prod_{j=0,\, j\neq i}^{n} \frac{x-x_j}{x_i-x_j} \end{aligned} \tag{2}$$

Step3: The approximate value $L(x)$ of the missing value can be obtained by substituting the x where the data is missing into the interpolation polynomial. Taking percentage of education expenditure as an example, the effect of data interpolation is shown in Tab.5.

Tab.5 The effect of data interpolation

Original		After data interpolation	
Time	Percentage of education expenditure	Time	Percentage of education expenditure
2009-03	10.88	2009-03	10.88
2009-06	12.40	2009-06	12.40
2009-09	missing	2009-09	13.25
2009-12	13.54	2009-12	13.54

5.3 Principal component analysis of policy indicators

Presidential candidates Trump and Biden have expressed different policy propositions in response to the COVID-19 fighting measures, international trade, and economic development. The election of different candidates will have different effects on economic development. We have selected corresponding indicators for each policy to reflect the impact of the policy. These policy indicators are important basis for describing the policy impact adopted by candidates. Each statistical indicator reflects part of the information about the economic situation under the corresponding policy, but not all the information is the main one, and because there is a certain correlation between the statistical indicators, dimensionality reduction and simplification are needed to extract some potential comprehensive indicators to describe economic conditions. This paper uses principal component analysis to process economic statistical indicators, and uses a few comprehensive indicators to fully reflect the information carried by each indicator.

(1) Principle of Principal Component Analysis

The principal component analysis method aims to remain the most important components in the original data in the process of dimensionality reduction, so as to maximize the variance of the original data, that is, to replace the original more single indicators with fewer comprehensive indicators, it is equivalent to replacing p indicators X_p with k principal components Y_k in mathematics, generally, these p indicators X_p are linearly combined to generate Y_k.

The information contained in a random variable can be measured by the degree of dispersion of its value (that is, the size of the variance), therefore, in principal component analysis, the largest ($Var(Y_1)$ is largest) variance among all linear combinations is used as the first principal component. If Y_1 is not enough to represent the original p indicators, consider extracting the next comprehensive indicator Y_2. In order to ensure the effectiveness of information extraction, make sure $Cov(Y_1, Y_2) = 0$, that is, Y_1 and Y_2 are not related, and Y_2 can independently reflect another aspect of information.

(2) Standardization of indicator variables

Before the principal component analysis, it is usually necessary to standardize each indicator variable, so as to avoid the unreasonable selection of the unit of equally important variables, which makes the variance of the unit huge, thus giving unreasonable principal component analysis results. Usually $\tilde{X} = \frac{X_i - E(X_i)}{\sqrt{D(X_i)}}$ is used to standardize indicator variables.

(3) Steps of Principal Component Analysis

Step1: Standardize raw index data

$$\tilde{X}_{ij} = \frac{X_{ij} - \bar{X}_i}{S_i} \tag{3}$$

$$\bar{X}_i = \frac{1}{n}\sum_{j=1}^{n} x_{ij} \qquad i = 1, 2, \ldots, n \tag{4}$$

$$s_i^2 = \frac{1}{n}\sum_{j=1}^{n} (x_{ij} - \bar{x}_i) \qquad i = 1, 2, \ldots, n \tag{5}$$

Get standardized data matrix

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1p} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2p} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \tilde{x}_{np} \end{pmatrix} \tag{6}$$

Step2: Calculate the correlation coefficient between each variable, and establish the correlation coefficient matrix R between the variables.

Step3: Solve the eigenvalues and eigenvectors of R. Solve the characteristic value

$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$ from $(\lambda I - R) = 0$, and then calculate the characteristic vector $l_1, l_2, \cdots, l_p$, $l_i = (l_{i1}, l_{i2}, \cdots l_{ip})^T$ from $(\lambda I - R) = 0$.

Step4: Calculate the contribution rate $p_i = \lambda_i / \sum_{i=1}^{p} \lambda_i$ and cumulative contribution rate $\sum_{j=1}^{k} p_j = \sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{p} \lambda_i$ of each principal component, and determine the number m of principal components to be used according to the 0.85 principle.

Step5: Write the expression of the principal component $Y_i = l_{i1}\tilde{X}_1 + l_{i2}\tilde{X}_2 + \cdots + l_{ip}\tilde{X}_p$. In order to make the principal component easier to explain, the load matrix of the principal component is rotated, and the maximum variance method is used to adjust the principal component load matrix after rotation.

Step6: Back to the original data, calculate the score of the selected principal component.

(4) Results of Principal Component Analysis

The KMO (Kaiser-Meyer-Olkin) calculated for 10 policy indicators is 0.754>0.6, and the significance value of Bartlett's Test of Sphericity is 0.000<0.05, indicating that the data is suitable for principal component analysis.

Through principal component analysis, the principal component contribution rate of 10 statistical indicators is obtained. From Tab.6 and Fig.1, it can be seen that cumulative contribution rate of the first three principal components exceeds 85%. From the gravel map of eigenvalues, Fig.2, it can be seen that eigenvalues corresponding to the first three principal components are all larger than 1. Principal components can use fewer indicators to reflect the information reflected by the original more indicators, so this paper selects the first 3 principal components to represent the original 10 policy indicators.

Tab.6 Principal component contribution rate

No.	Variance	contribution rate /%	cumulative contribution rate /%
1	6.423	64.235	64.235
2	1.568	15.678	79.912
3	1.116	11.160	91.072
4	0.392	3.921	94.994
5	0.218	2.182	97.176
6	0.131	1.305	98.481
7	0.086	0.858	99.339
8	0.046	0.457	99.796
9	0.014	0.135	99.931
10	0.007	0.069	100.000

The correlation coefficients between the first three principal components and policy indicators are shown in Tab.7, and the characteristic values reflected by each principal component are as follows:

1) The first principal component mainly reflects: infrastructure investment, average CO_2 emissions, average domestic general government health expenditure, unemployment rate, trade deficit, Stock price general 500 index, total number of international migrants, which are comprehensive indicators reflecting policies.

2) The second principal component mainly reflects: total import and export, trade deficit, and percentage of education expenditure.

3) The third principal component mainly reflects: tax income, unemployment rate, total import and export.

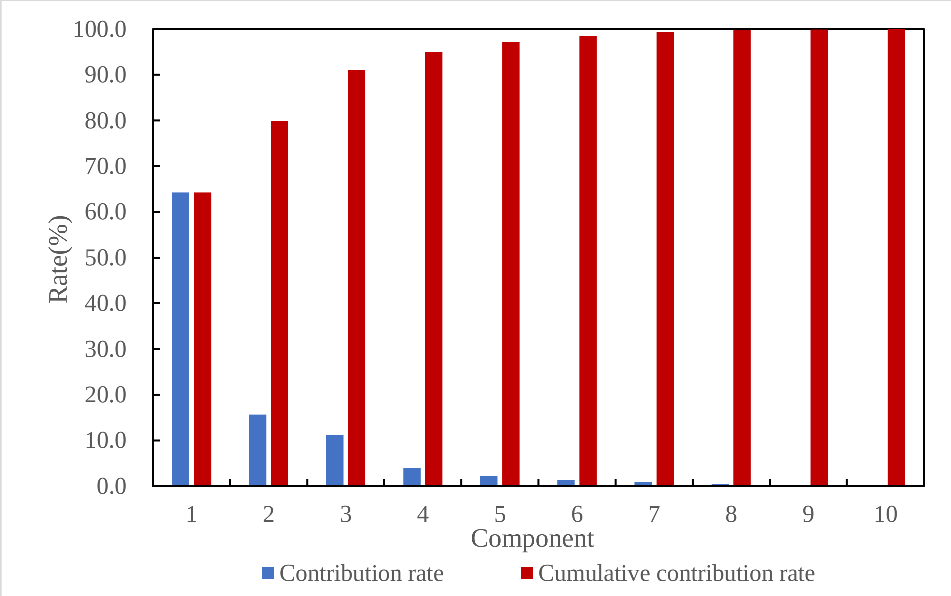

Fig.1 Principal component contribution rate analysis

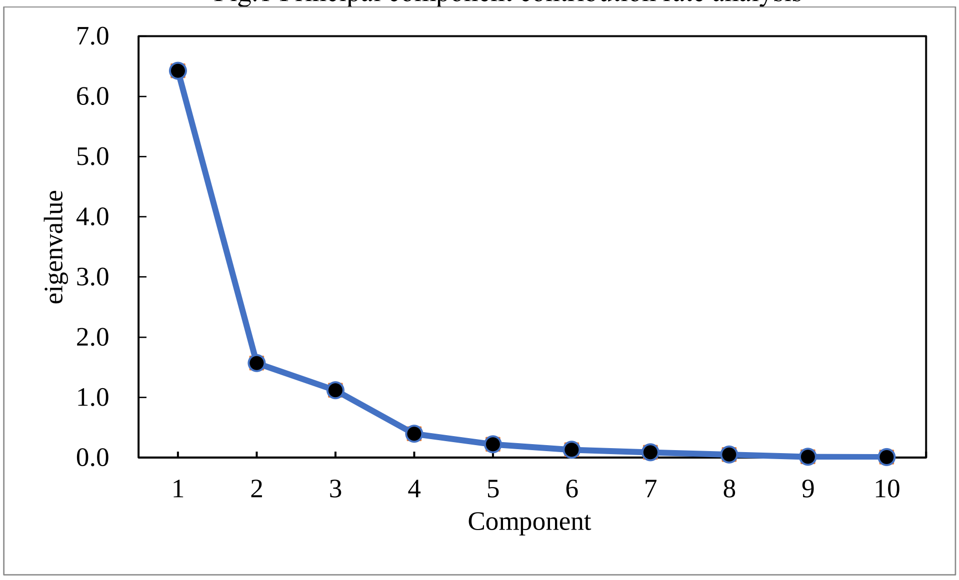

Fig.2 Gravel diagram of principal component analysis

Tab.7 Principal component load matrix after rotation

Policy indicators	The first principal component	The second principal component	The third principal component
X_1	0.947	0.259	0.064
X_2	0.349	0.072	0.898
X_3	-0.928	-0.176	-0.104
X_4	0.881	0.391	0.165
X_5	-0.722	-0.309	0.534
X_6	0.465	0.716	-0.369
X_7	0.685	0.615	0.071
X_8	0.877	0.393	0.201
X_9	0.920	-0.166	0.102
X_{10}	0.007	0.934	0.097

5.4 Prediction of principal component indicators based on BP Neural Network

This paper uses the BP neural network method to fit and predict the principal component indicators of the two presidential candidates after the election of Trump and Biden respectively, and obtain the prediction results to prepare for the subsequent economic indicator prediction based on the VAR model.

5.4.1 Determination of training and testing sample data

(1) Training sample S_1

Considering that Biden served as the vice president of the United States during the Obama administration, and at the same time, combining the policy propositions put forward by Biden during the campaign and comparing them with the policies of Obama, the results obtained are shown in Tab.8. Among them, 1 means that the policies of Biden and Obama are similar, and 0 means that they are not similar.

Tab.8 Comparison of similarities between Biden and Obama's policies

Policy indicators	Similarities	Policy indicators	Similarities
immigration	1	environmental	1
trade	1	medical insurance	1
diplomacy	0	education	1
economy and employment	1	infrastructure	1

According to Tab.8, regardless of the impact of COVID-19, the similarities between Biden and Obama's policies are as high as 87.5%. Therefore, the data from 2008 to 2016 during the Obama administration is used as the training sample of candidate Biden.

(2) Training sample S_2

The collected data from 2008 to 2020 was used as the training sample of candidate Trump. The reason for this is that S_2 not only considers the impact of historical policy data, but also considers the characteristics of Trump's governance. Therefore, it is more reasonable to use S_2 to predict Trump's policy data after the election.

(3) Testing sample T

In order to test the fitting accuracy of BP Neural Network, it is necessary to select test samples for testing. This paper selects the policy data of Trump's four years in power as the test samples. The main reasons are as follows:

1) T is close to the year of the data to be predicted, which is conducive to the subsequent fitting and prediction.

2) T makes up for the shortcomings of S_1, so that the forecast of policy indicators after Biden's election will not deviate from the status quo of Trump's administration.

5.4.2 Forecasting algorithm based on BP Neural Network

BP Neural Network can approximate any non-linear mapping with arbitrary precision, and has learning and self-adaptability. The connection value of the network can be modified to respond to changes in the system. In addition, the multi-input multi-output network constructed by it has good fault tolerance and can generate a system with strong robustness. Because of the above characteristics, BP Neural Network is widely used, can better adapt to the system characteristics of the multi-index variable of this problem, and makes it possible to predict the policy indicators of the two presidential candidates in the next term.

The BP neural network mainly includes three layers: input layer, hidden layer, and output layer. Each layer is composed of many parallel computing neurons. The principle is: the working signal obtains the network error through forward propagation, and the error signal passes back propagation to feed back the adjustment network. In the process of forward propagation, the working signal input by the input layer is transformed by the hidden layer and transmitted to the output layer, and the output signal is obtained at the output end. If the output signal obtained does not meet the given standard, then the error back propagation process is performed. The difference between the actual output value obtained by the forward operation and the expected output value is used as the error signal, which is transmitted from the output layer to the input layer. In this process, the error signal is continuously fed back to adjust the network weight, and the ideal output value is obtained by continuously correcting the weight. The three-layer BP neural network structure is shown in Fig.3.

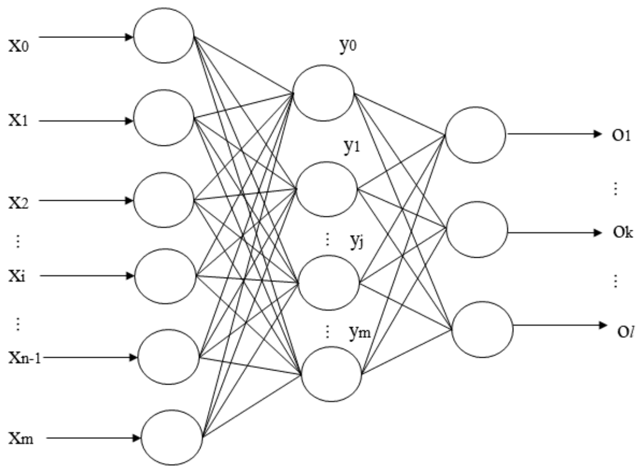

Fig.3 Three-layer BP Neural Network structure

According to the working principle of BP Neural Network, the following algorithm is designed:

Step1: Clarify the input and output variables and corresponding parameters: $X_k = [x_{k1}, x_{k2}, \dots x_{kM}]$, $(k = 1, 2, \dots, N)$ represents the input signal of the input layer, Where N is the number of samples (Biden is 32, Trump is 47), M is the number of main modeling variables (10). The weight matrix during iteration is shown in formula (7).

$$W_{IJ}(t) = \begin{bmatrix} w_{01}(t) w_{02}(t) \dots w_{0J}(t) \\ w_{11}(t) w_{12}(t) \dots w_{1J}(t) \\ \dots \\ w_{I1}(t) w_{I2}(t) \dots w_{IJ}(t) \end{bmatrix} \quad W_{JK}(t) = \begin{bmatrix} w_{01}(t) w_{02}(t) \dots w_{0K}(t) \\ w_{11}(t) w_{12}(t) \dots w_{1K}(t) \\ \dots \\ w_{J1}(t) w_{J2}(t) \dots w_{JK}(t) \end{bmatrix} \tag{7}$$

They respectively represent the weight matrix corresponding to the input layer I to the hidden layer J and the weight matrix corresponding to the hidden layer J to the output layer K at the t^{th} iteration.

$O_n(t) = [o_{n1}(t) o_{n2}(t) \dots o_{np}(t)], (n = 1, 2, \dots N)$ represents the output vector of the network at the t^{th} iteration.

$D_n(t) = [d_{n1}(t) d_{n2}(t) \dots d_{np}(t)], (n = 1, 2, \dots N)$ represents the output vector that the network operation should get.

Step2: Construct the initial network, use the method of randomly assigning smaller values to the network weights, assign the weight matrix $W_{IJ}(0)$, $W_{JK}(0)$ to the smaller non-zero matrix. The input and output data are respectively standardized and transformed into training samples and expected output that can be directly used in calculations. This paper uses linear normalization method to process the data, the formula is as follows:

$$x^* = \frac{(y_{\max} - y_{\min})(x - x_{\min})}{x_{\max} - x_{\min}} + y_{\min} \tag{8}$$

Step3: Randomly draw samples X_k from the training samples, and the corresponding expected output D_k.

Step4: Take the input sample X_k as an example, through the forward operation of the neurons in each layer of BP Neural Network, the input signal μ and the output signal v are obtained, $o_{nk}(t) = v_k^K(t)$. The transmission of each signal in the hidden layer needs to pass the activation function. In this paper, the Sigmod function is selected as the activation function, and the formula is as follows:

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Step5: Make the difference between the network output $O_n(t)$ obtained by the forward operation of the BP neural network and the given expected output $D_n(t)$ to get the network relative error $E(t)$, and judge whether it meets the accuracy requirements, if it meets the requirements, go to Step 8; otherwise, go to Step 6.

Step6: Judge whether $(t+1)^{th}$ iteration meets the termination condition. If it does, go to Step 8. If it does not, use the input sample to calculate the local gradient value of each layer of neurons through the error back propagation process.

$$\delta_k^K(t) = o_{nk}(t)(1 - o_{nk}(t)) \cdot (d_{nk}(t) - o_{nk}(t)) \tag{10}$$

$$\delta_j^J(t) = f'(\mu_j^J(t)) \sum_{k=1}^{K} \delta_k^K(t) \cdot w_{jk}(t) \tag{11}$$

Step7: Use the learning rate η to calculate the weight correction and correct the corresponding weight matrix. Go to Step4, and the weight correction method is as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j^J(t) \cdot x_{ni}(t) \tag{12}$$

$$w_{jk}(t+1) = w_{jk}(t) + \eta \delta_k^K(t) \cdot v_k^K(t) \tag{13}$$

Step8: Judge whether the training samples are all completed, if yes, end the calculation, otherwise go to Step3.

5.4.3 Performance optimization of BP Neural Network

(1) Performance optimization of BP Neural Network in training set S_1

The number of neurons in the hidden layer of the BP neural network has a great influence on whether the network converges, the speed of convergence, and the accuracy of the results. However, so far there is no sufficient theoretical basis to show how to determine the number, and the selection is generally determined by relying on past experience. In this paper, by adjusting the number of hidden layer neurons and training samples, different neural network structures are constructed, and the number of iterations required by each network and the correlation coefficient R^2 are obtained, then find the number of hidden layer neurons that makes the BP neural network performance optimal. Because the relationship between the variables is complicated, after preliminary experiments, this paper sets the number of neurons between [5,20].

Taking the principal component Y_1 as an example, Tab.9 shows the corresponding calculation results of different network structures when the number of neurons is adjusted.

Tab.9 Number of iterations and correlation coefficients of different BP Neural Networks-Y_1

Number of neurons	Number of iterations	Correlation coefficients	Number of neurons	Number of iterations	Correlation coefficients
5	10	0.513486	13	32	0.287622
6	8	0.504419	14	19	0.553445
7	16	0.476102	15	12	0.53719
8	9	0.526028	16	11	0.686481
9	8	0.527933	17	7	0.59794
10	9	0.530223	18	9	0.496559
11	9	0.555294	19	15	0.552295
12	8	0.554874	20	23	0.421812

It can be seen from Tab.9 that when the number of neurons in the hidden layer is 16, the correlation coefficient of the BP neural network model reaches the maximum, indicating that the error with the Trump administration is the smallest at this time. Therefore, for the principal component Y_1, it is more reasonable when the number of hidden layer neurons is 16.

In the same way, the reasonable number of hidden layer neurons of the principal components Y_2 and Y_3 can also be obtained by testing. In summary, the performance optimization results of all principal components of the BP Neural Network are shown in Tab.10.

Tab.10 BP Neural Network performance optimization results of each principal component-S_1

Principal component	Number of neurons	Number of iterations	Correlation coefficients
Y_1	16	10	0.6865
Y_2	20	10	0.7567
Y_3	14	8	0.6575

(2) Performance optimization of BP Neural Network in training set S_2

The performance of the BP Neural Network is optimized on the training set S_2 using the previous method, and the results are shown in Tab.11.

Tab.11 BP Neural Network performance optimization results of each principal component-S_2

Principal component	Number of neurons	Number of iterations	Correlation coefficients
Y_1	13	274	0.6435
Y_2	15	22	0.7835
Y_3	11	21	0.7564

5.4.4 Neural network testing and verification

For the training sets S_1 and S_2, the BP neural network performance optimization results determined in Table 10 and Table 11 are used to test the fitting degree of T. Under the training sets S_1 and S_2, the comparison between the test sample and the prediction result about the three principal components Y_1, Y_2, and Y_3 is obtained, as shown in Fig.4-Fig.6.

As can be seen, the overall gap between the predicted value of each principal component and the actual value is small, and the fluctuation direction of the curve tends to be the same, indicating that the model has high accuracy, good prediction effect, and high reliability of the predicted value data obtained. However, there are also some problems at the same time. For example, there is a gap between the predicted values and actual values in the last three samples of the test set in Fig.4 and Fig.6. The main reason is the impact of COVID-19:

(1) Affected by the epidemic, the overall economic level of the United States has shown a downward trend, which has caused a sudden change in the main component Y_1 in March 2020.

(2) Affected by the epidemic, the number of unemployed persons and the unemployment rate in the United States have soared. Y_3 mainly reflects the unemployment rate, so Y_3 also has a sudden change in March 2020.

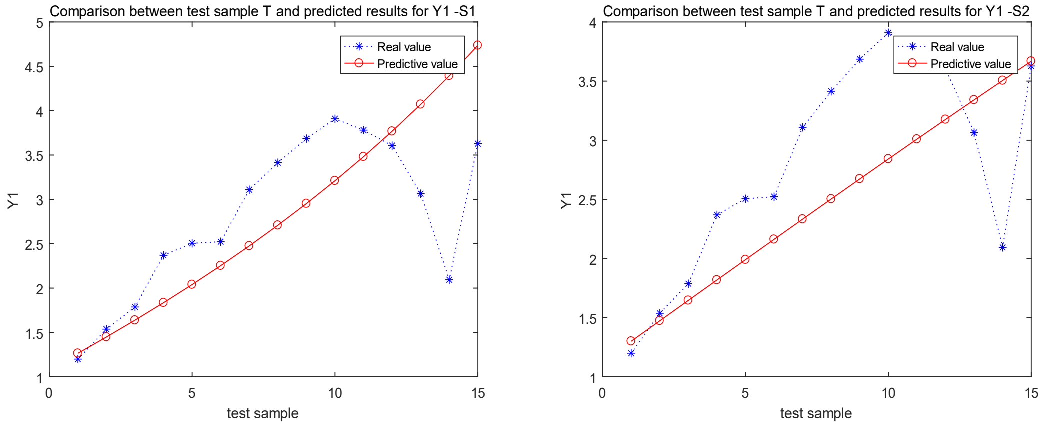

Fig.4 Comparison of test samples and prediction results under the two training sets of Y_1

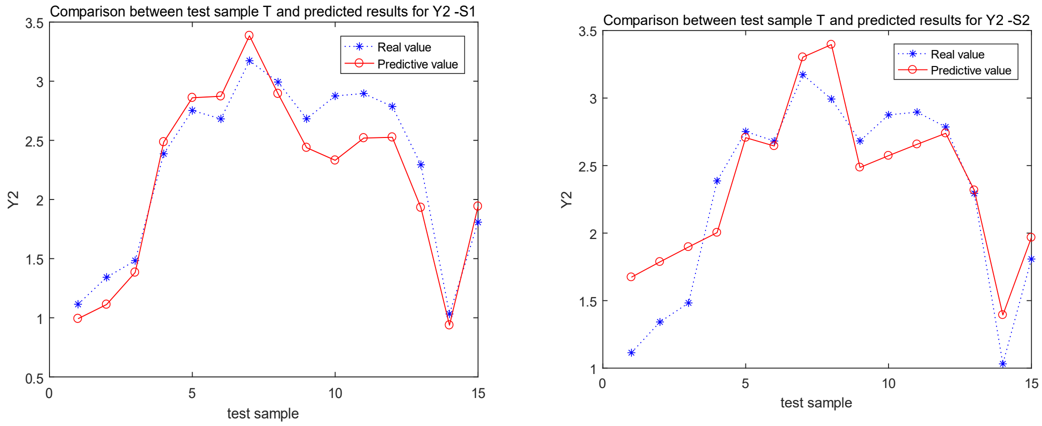

Fig.5 Comparison of test samples and prediction results under the two training sets of Y_2

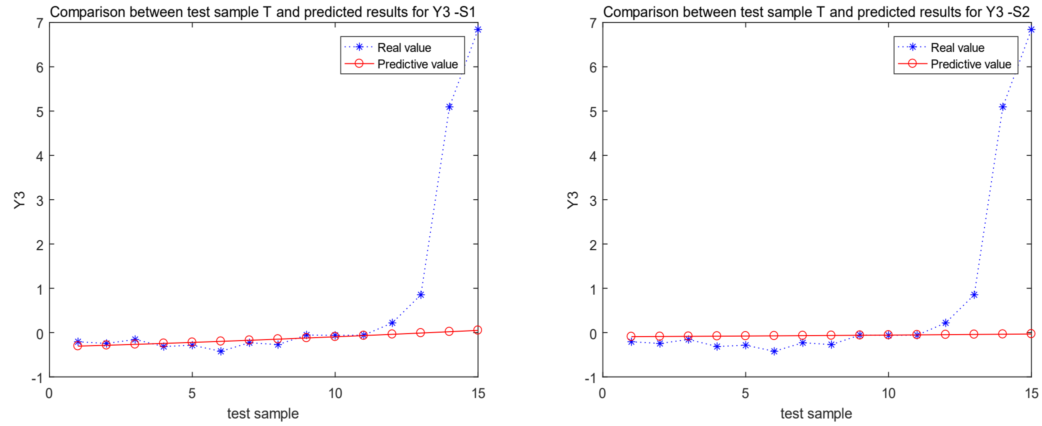

Fig.6 Comparison of test samples and prediction results under the two training sets of Y_3

5.4.5 Adjustment of BP Neural Network considering COVID-19

COVID-19 has caused a sudden change in US policy indicators. In order to add the impact of COVID-19 to the original results, this article interpolates the values of the three quarters of 2020 on the existing basis and reconstructs BP Neural Network for adjustment. Test the data of the test sample under this adjusted neural network, and the results of Y_1 and Y_3 are shown in Fig.7-Fig.8.

As can be seen from the figure, the adjusted BP Neural Network takes into account the impact of COVID-19, which is more consistent with the actual situation.

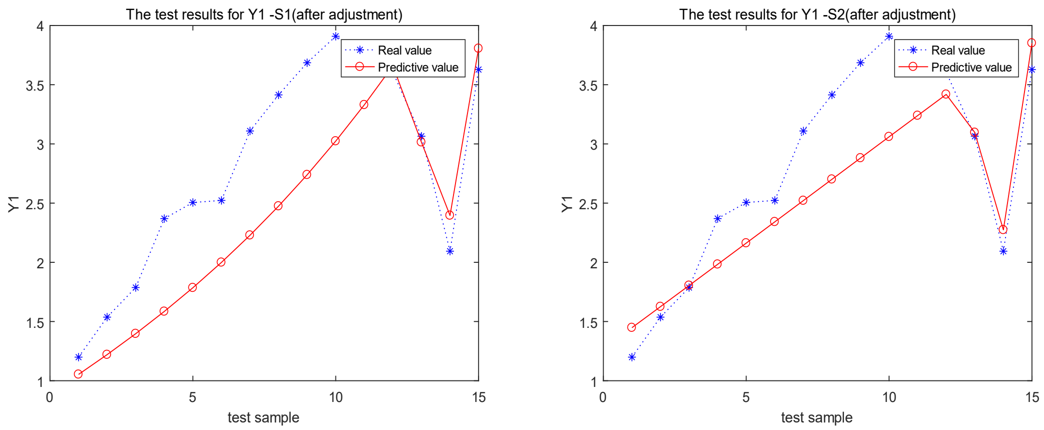

Fig.7 Y_1 test results after adjusting the neural network

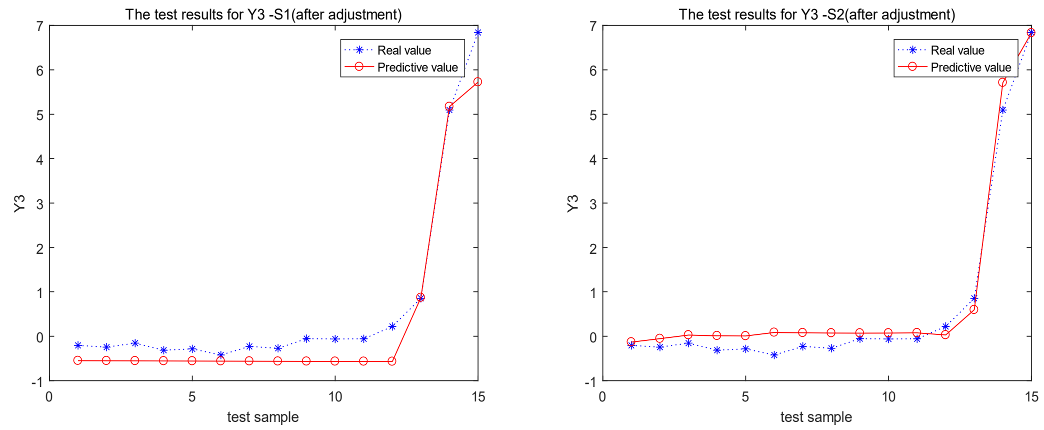

Fig.8 Y_3 test results after adjusting the neural network

5.4.6 Policy indicators prediction based on adjusted BP Neural Network

According to the adjusted BP Neural Network, the subscript of the simulation test is changed to: from the beginning of the forecast quarter to the end of the last quarter of 2024. After Biden and Trump are elected, the predicted values of each principal component of the next four years are shown in Tab.12.

Tab.12 The predicted values of all principal components for the next four years

Time	Biden			Trump		
	Y_1	Y_2	Y_3	Y_1	Y_2	Y_3
2020-12	2.2028	2.0065	0.4706	1.3955	3.5142	0.7487
2021-03	2.2723	2.4435	0.2109	1.5682	3.7431	0.8419
2021-06	2.3438	3.0068	0.0109	1.6337	3.9803	0.7122
2021-19	2.4180	3.5992	-0.3110	1.9806	4.2261	0.3438
2021-12	2.4956	3.9238	-0.4211	2.0817	4.4806	0.1337
2022-03	2.5772	4.2839	-0.4711	2.2203	4.7443	0.0351
2022-06	2.6636	4.6829	-0.4710	2.7273	5.0174	-0.3386
2022-09	2.7554	5.1246	-0.4709	2.9036	5.3002	-0.4442
2022-12	2.8535	5.6131	-0.4708	3.0502	5.5930	-0.4422
2023-03	2.9586	6.1524	-0.4706	3.1684	5.8961	-0.4402
2023-06	3.0716	6.7467	-0.4704	3.2591	6.2099	-0.4392
2023-09	3.1934	7.4005	-0.4702	3.3237	6.5346	-0.4342
2023-12	3.3249	8.1182	-0.4698	3.3634	6.8707	-0.4042
2024-03	3.4671	8.9041	-0.4695	3.3794	7.2184	-0.4014
2024-06	3.6210	9.7625	-0.4690	3.3731	7.5781	-0.4012
2024-09	3.7877	10.6973	-0.4686	3.3459	7.9501	-0.4011
2024-12	3.9685	11.7121	-0.4680	3.2991	8.3349	-0.4011

5.5 Economic indicators prediction based on VAR Model

This section aims to analyze the relationship between principal component indicators and economic indicators, and then based on the values of the principal component indicators predicted by the BP Neural Network above, the predicted values of various economic indicators in the United States in the next stage can be obtained, and then the economic development trends of the United States when different candidates are elected can be quantitatively analyzed. Vector Autoregressive Model (VAR) is widely used in economics. It mainly uses actual economic data to determine the dynamic structure of the economic system. It is often used to analyze the relationship between interconnected indicators and the impact of random disturbances on the economic system. In view of the built-in VAR model in the economic software EViews10, this paper uses EViews10 software to establish a VAR-based prediction model of US economic indicators. The specific steps are as follows:

Step1: Test the stationarity of the data series, which is the prerequisite for establishing the VAR model. Import historical data of principal component indicators Y1, Y2, Y3 and economic indicators GDP, PPI, and A_GNI into EViews10, and use the ADF test method to test the stationarity of each item one by one. The criterion for passing the test is that the Prob under level or first difference is less than 0.5. The test results are shown in Tab.13, it can be seen that all the series pass the stationarity test.

Tab.13 Sequence stationarity test results

Sequence	Order	t-Statistic	Prob
GDP	level	-4.211361	0.0090
PPI	first difference	-9.192985	0.0000
A_GNI	level	-4.081910	0.0127
Y1	level	-3.702587	0.0321
Y2	level	-3.690424	0.0333
Y3	first difference	-3.821201	0.0248

Step2: Determining the optimal lag order is an important problem that the VAR model needs to solve. The larger the lag order, the more fully utilized the information, but the freedom degree of the model will decrease, the lag order can be determined according to criteria such as LR, AIC, and SC. This paper integrates multiple criteria in EViews10 to determine the optimal lag order, assuming that the maximum lag order is 5, the values of each criterion are as shown in Tab.14 (take two decimal places; * indicates the optimal lag order selected by the corresponding criterion, the order with the most marked times is the optimal value), and the optimal lag order is 2.

Tab.14 Lag order determination result

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-351.58	NA	265.36	16.93	17.10	16.99
1	-211.72	246.42	0.73	11.03	11.86	11.34
2	-158.99	82.86*	0.13	9.29	10.77*	9.83*
3	-141.15	24.64	0.13	9.20	11.35	9.99
4	-124.43	19.90	0.14	9.16	11.98	10.19
5	-99.43	25.01	0.11*	8.73*	12.21	10.01

Step3: Establish a VAR model with a lag order of 2, and get the relationship between GDP and Y_1, Y_2, and Y_3 as shown in the equation (the coefficients retain two decimal places).

$$\begin{aligned} GDP(t) = &-0.45GDP(t-1) + 0.84GDP(t-2) + 259.10Y_1(t-1) - 102.19Y_1(t-2) \\ &+3.02Y_2(t-1) - 11.90Y_2(t-2) - 142.00Y_3(t-1) + 37.25Y_3(t-2) + 2745.08 \end{aligned} \tag{14}$$

Similarly:

$$\begin{aligned}PPI(t)=&-0.34PPI(t-1)+0.04PPI(t-2)+0.35PPI(t-3)\\&+5.71Y_1(t-1)-6.25Y_1(t-2)+1.95Y_1(t-3)\\&-0.83Y_2(t-1)+3.43Y_2(t-2)-1.83Y_2(t-3)\\&-10.85Y_3(t-1)-2.75Y_3(t-2)+5.62Y_3(t-3)+90.23\end{aligned}\tag{15}$$

$$\begin{aligned}A\_GNI(t)=&0.87A\_GNI(t-1)-1.17A\_GNI(t-2)-1.52A\_GNI(t-3)\\&+0.15A\_GNI(t-4)+1.10A\_GNI(t-5)+8951.40Y_1(t-1)\\&-6076.37Y_1(t-2)+3514.18Y_1(t-3)-1322.38Y_1(t-4)\\&+821.06Y_1(t-5)-4080.84Y_2(t-1)+3168.15Y_2(t-2)\\&-1250.89Y_2(t-3)+1233.70Y_2(t-4)-1304.08Y_2(t-5)\\&-7473.31Y_3(t-1)-4625.25Y_3(t-2)+10934.90Y_3(t-3)\\&-4265.30Y_3(t-4)-6841.72Y_3(t-5)+85461.90\end{aligned}\tag{16}$$

Substituting historical data and the predicted values of principal component indicators, the predicted results of each economic indicator are shown in Tab.15 and Fig.9-Fig.11.

Tab.15 The predicted values of various economic indicators

Time	GDP（billion dollars）		PPI		A_GNI（dollar）	
	Trump	Biden	Trump	Biden	Trump	Biden
2020-12	5086.81	5086.81	101.9951	101.9951	47432.59	47432.59
2021-03	4805.535	5049.639	74.34591	83.22399	40863.95	56321.35
2021-06	4999.88	5082.009	109.8216	109.3108	45475.46	56848.98
2021-19	4695.577	5063.232	91.04404	99.70397	45409.56	51808.63
2021-12	5124.533	5144.604	96.14367	100.7749	49034.48	54164.56
2022-03	4680.776	5102.774	107.3704	110.9566	52392.94	53456.89
2022-06	5270.522	5203.659	97.80077	103.064	46903.04	56414.29
2022-09	4796.86	5132.503	108.8678	106.4886	55694.66	61316.42
2022-12	5498.171	5261.135	108.5957	108.773	57584.03	64017.64
2023-03	4798.222	5156.069	104.8989	105.8991	58022.41	58075.04
2023-06	5715.377	5324.805	109.7317	108.7453	54046.78	64438.78
2023-09	4723.659	5174.945	108.1466	109.0967	51748.34	67423.44
2023-12	5944.629	5399.478	107.8199	108.7799	54751.49	61430.04
2024-03	4559.166	5189.061	109.4828	110.6576	59258.02	68374.59
2024-06	6206.385	5490.132	108.5009	110.9594	60304.37	74748.27
2024-09	4295.391	5197.08	109.1625	111.7259	68317.84	80234.17
2024-12	6529.724	5602.581	109.6949	113.1192	70634.08	79265.53

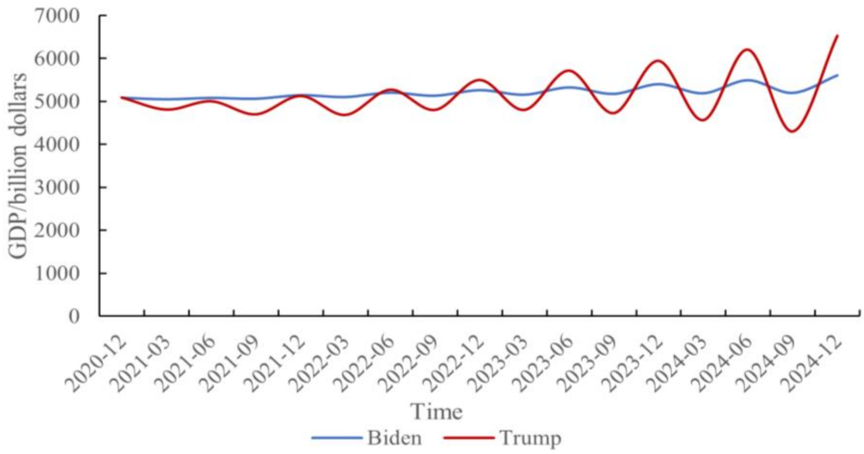

Fig.9 Comparison of GDP prediction results

The analysis of the impact of different candidates on GDP is as follows:

(1) GDP overall volatility

Comparing Biden and Trump's overall GDP change trend during the post-election term, we can find that Biden's overall GDP volatility after election is relatively small. The reason is that Biden pays more attention to the independence of the Federal Reserve and has stricter currency supervision. In other words, Biden's economic policies tend to be more conservative.

(2) Total GDP during the tenure

Comparing Biden's and Trump's total GDP in the post-election terms, Biden's is 8,8660.5 (billion dollars), and Trump's is 8,7731.2. Compared to Trump, Biden's total GDP is slightly larger. The reason is that Biden has adopted stricter anti-epidemic measures relative to Trump. Therefore, the GDP rebound in 2021 is more obvious, which makes GDP return to normal levels as soon as possible. This also causes the total GDP of Biden to be slightly larger.

(3) GDP comparison at the beginning of the tenure

Comparing Biden's and Trump's GDP at the beginning of the tenure, it can be found that Trump's GDP at the beginning of his term is lower than that of Biden. The reason is that Trump continues to adopt loose anti-epidemic policies, which has led to the continued sluggish GDP trend during his tenure.

(4) GDP comparison at the end of tenure

Comparing Biden's and Trump's post-election GDP at the end of the term, it can be found that Trump's GDP is higher than that of Biden. The reason is that Trump adopts loose economic policies, and implements comprehensive tax cuts and loose monetary, fiscal, and financial supervision policies. Therefore, the economic bubble is higher than that of Biden.

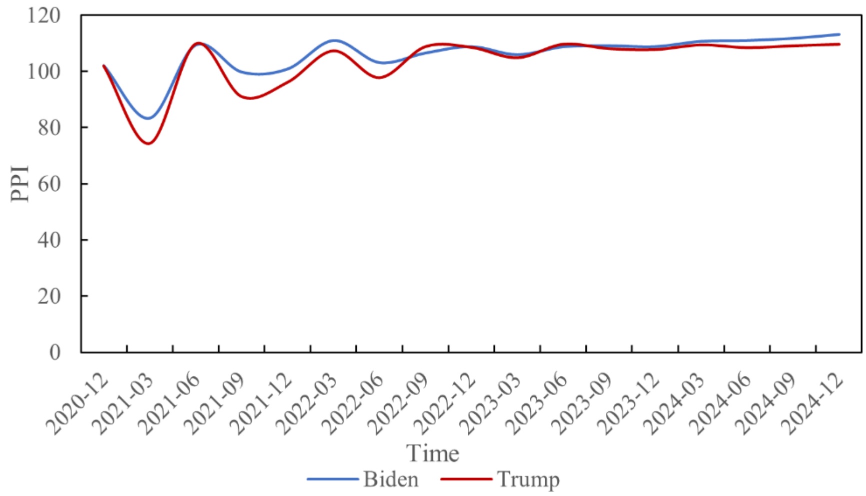

Fig.10 Comparison of PPI prediction results

The analysis of the impact of different candidates on PPI is as follows:

(1)On the macro level, the election of Trump and the election of Biden have basically the same impact on the PPI, because no matter who is elected, there is a high probability that the fifth round of financial relief plan will be required to deal with the impact of the epidemic on the US economy. In the short term, it will increase inflation in the United States, thereby reducing PPI.

(2) At the micro level, Trump's inadequate attention to the epidemic will lead to greater volatility in his PPI than when Biden is elected. Eventually, with the gradual control of the global epidemic and the acceleration of vaccine research and development, the changes in PPI will gradually stabilize and the US economy will gradually stabilize.

The analysis of the impact of different candidates on A_GNI is as follows:

When Biden is elected president of the United States, the predicted value of A_GNI is larger than that of Trump. This is because Biden's plan to increase taxes on the rich and companies and raise the minimum wage is conducive to reducing the gap between the rich and the poor and increasing A_GNI, while Trump advocates tax cuts that benefit the rich even more, which is not conducive to the increase in A_GNI.

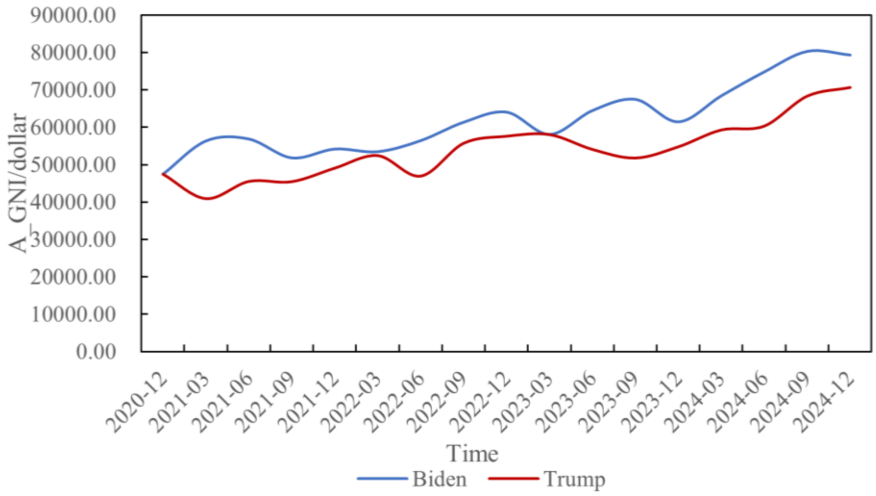

Fig.11 Comparison of A_GNI prediction results

6 Modeling and solution of problem two

6.1 Comparison of policies towards China

Biden and Trump have more consensus on China policy, but Biden has a clear welcome attitude towards cooperation in areas of common interests between China and the United States. The following is a comparison of the two candidates' views on China policy in terms of COVID-19 epidemic prevention policy, taxation, energy and environmental protection, science and technology, trade, finance and education.

Tab.16 Comparison of U.S. presidential candidates' views on China Policy

Policy	Trump	Biden
COVID-19 epidemic prevention policy	Reducing cooperation between China and the US in epidemic prevention	China should be responsible for the adverse epidemic prevention, but strengthen the cooperation between China and the United States on epidemic situation
Tax revenue	Punitive tariffs on Chinese goods	Against the tariff fortress, but some aspects still impose tariffs
Energy and environmental protection	Pay attention to the development of traditional energy, and do not care about environmental protection	Cooperation with China on climate change and clean energy
Science and technology	Imposing scientific and technological sanctions on China and suppressing China's science and technology industry	Increasing restrictions on China's technological progress
Trade	Continue the trade war with China and adhere to trade protectionism	China and the United States should ease trade frictions and put pressure on China through the cooperation of trade allies
Finance	Reducing investment in China and preventing Chinese enterprises from going to the United States for listing	Oppose financial sanctions against China
Education	Against Chinese students going to the United States	Accepting Chinese students

6.2 Data acquisition and preprocessing

The second question requires a quantitative analysis of the impact of the election of different candidates on China's economy. Therefore, it is necessary to obtain the indicator data that can easily reflect the impact of the U.S. policy on China in China's economy.

The data obtained should include two aspects:

(1) Policy index data that can reflect the impact of China's policy changes, and the data structure is shown in Tab.17;

(2) The economic index data representing China's economic changes, mainly considering China's Total Import and Export Trade(TIE) and Customs Duties(CD), and the data structure is shown in Tab.18. After extensive data collection, the complete data results obtained are shown in Attachment 1, and the data source is Zhonghong statistical database.

Tab.17 Data structure of China policy indicators

Time(quarterly)	Z_1(100 million tons)	Z_2(thousands of US dollars)	Z_3	Z_4(%)

Tab.18 Data structure of China's economic indicators

Time(quarterly)	TIE(US $100 million)	CD(RMB 100 million)

Some of the data obtained in question 2 also lack some quarterly data values, so the same Lagrange interpolation method is used to interpolate the missing values.

6.3 Fitting and forecasting of policy indicators value based on BP Neural Network

Because the number of China policy indicators is small, so it is no longer the same as the first question of principal component analysis, directly using BP neural network to fit and forecast the China policy indicators of Trump and Biden presidential candidates in the next term of office, and get the prediction results, which is prepared for the subsequent prediction of China's economic indicators based on VAR model.

6.3.1 Determination of training and testing sample data

(1) Training sample S_3

Considering that Biden served as vice president of the United States during the Obama administration, and combined with Biden's China policy during the election campaign, and compared with the China policy of Obama's period, the results are shown in Tab.19. Among them, 1 represents that Biden's policies are similar to those of Obama, and 0 represents that they are not.

Tab.19 Comparison of policy similarities between Biden and Obama

Policy	Similar or not	Policy	Similar or not
Tax revenue	1	Trade	1
Energy and environmental protection	1	Finance	0
Science and technology	1	Education	1

Novel coronavirus pneumonia is not considered in the above table. The similarity between Biden and Obama in China during the period of administration is also very high, reaching 83.3%. Therefore, we use the data related to Obama's China policy from 2008 to 2016 as a training sample for Biden, named S_3.

(2) Training sample S_4

The collected data on China policy from 2008 to 2020 are used as training samples for candidate Trump, named S_4.

(3) Test sample U

Similar to the first question, this paper selects the data of Trump's China policy for four years as the test sample.

6.3.2 Performance optimization of BP Neural Network

(1) Performance optimization of BP neural network based on training set S_3

Using the first question to adjust the number of neurons and training samples in the hidden layer, the correlation coefficient value corresponding to the number of neurons in each hidden layer is obtained, and the number of neurons with the maximum correlation coefficient is selected to construct the corresponding neural network. The performance optimization results of BP Neural Network for all China policy indicators are shown in Tab.20.

Tab.20 Performance optimization results of BP Neural Network

Policy indicators on China	Number of neurons	Number of iterations	Correlation coefficient
Z_1	15	7	0.995193
Z_2	13	245	0.712234
Z_3	13	8	0.992345
Z_4	20	11	0.822344

(2) Performance optimization of BP neural network based on training set S_4

According to the above method, the BP neural network performance optimization of training set S_4 is carried out, and the results are shown in the Tab.21.

Tab.21 Performance optimization results of BP Neural Network

Policy indicators on China	Number of neurons	Number of iterations	Correlation coefficient
Z_1	13	35	0.970633
Z_2	20	9	0.631422
Z_3	15	18	0.875645
Z_4	19	172	0.883397

6.3.3 BP Neural Network test and verification

Aiming at the training set S_3 and S_4, the fitting degree of U (test sample) is tested according to the optimization results of BP neural network determined in Tab.20 and Tab.21 respectively. Under the training set S_3 and S_4, the comparison between the test samples and the prediction results on the four China policy indicators Z_1, Z_2, Z_3 and Z_4 is obtained, as shown in Fig.12-Fig.15.

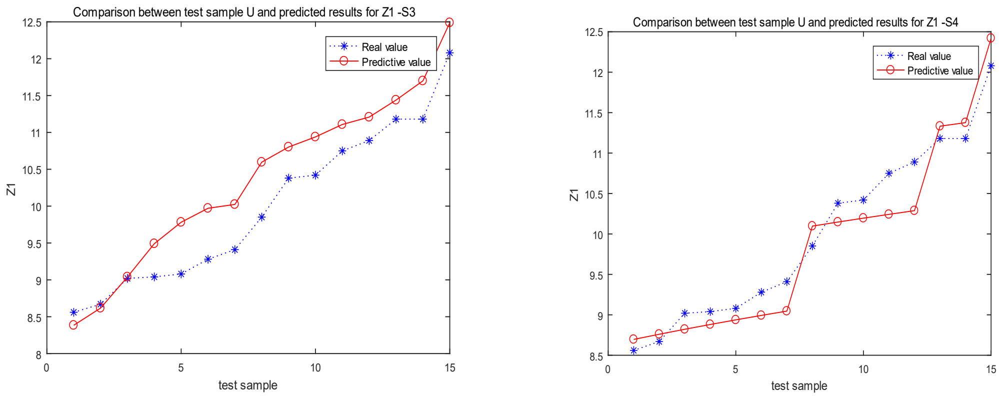

Fig.12 Comparison of test sample and prediction result Z_1 under two training sets

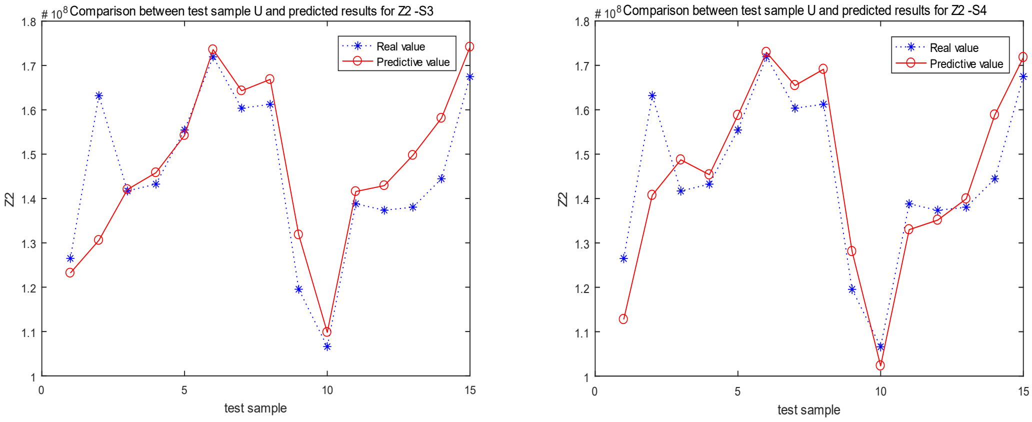

Fig.13 Comparison of test sample and prediction result Z_2 under two training sets

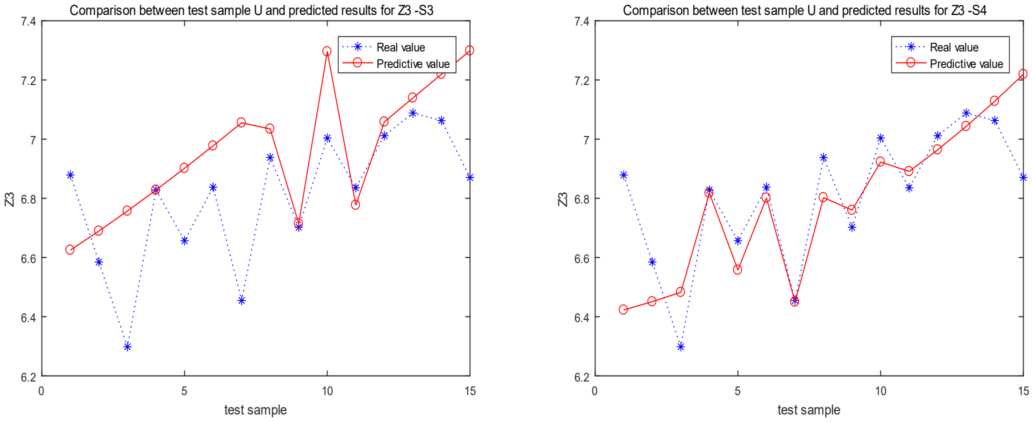

Fig.14 Comparison of test sample and prediction result Z_3 under two training sets

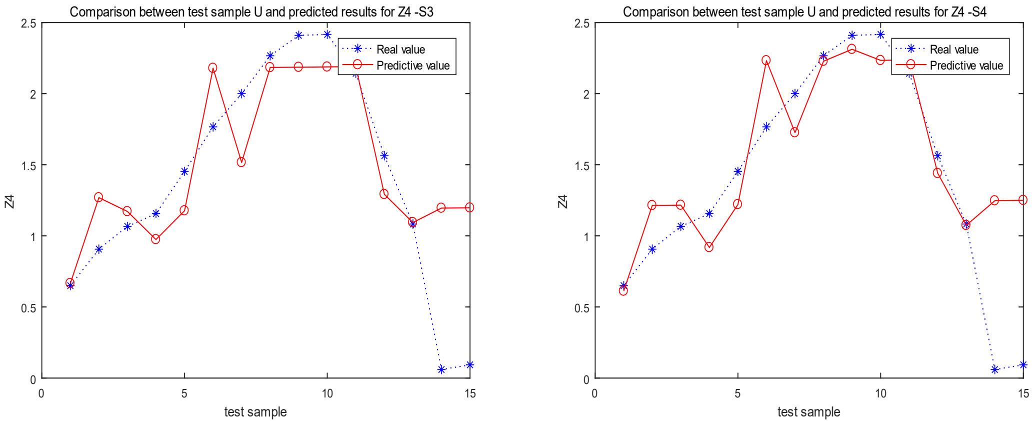

Fig.15 Comparison of test sample and prediction result Z_4 under two training sets

It can be seen from the above figure that the overall gap between the predicted value and the actual value of China policy indicators is small, and the fluctuation direction of the curve tends to be consistent, which indicates that the accuracy of the model is high, the prediction effect is good, and the predicted value data credibility is high. Novel coronavirus pneumonia is also the same problem as the first question. For example, there is a gap between the predicted value and the actual value of the final 3 samples of the test set 1 and 2. The main reason is the impact of COVID-19 epidemic:

(1) Affected by the epidemic situation, the overall economic level of the United States has

shown a downward trend. Due to the remarkable effect of epidemic prevention and control and rapid economic recovery in China, the exchange rate of US dollar against RMB has declined, the US dollar has depreciated, and the RMB has appreciated, resulting in the mutation of Z_3 in March 2020.

(2) Affected by the epidemic, the U.S. economy is going down, and the Federal Reserve adopts a zero interest rate policy, so the federal reserve fund interest rate continues to be low, resulting in a sudden change in Z_4 in March 2020.

6.3.4 Adjustment of BP Neural Network considering COVID-19

In order to add the influence of the new epidemic situation to the original results, BP Neural Network was adjusted according to question 1, and the test results of Z_3 and Z_4 after adjustment were obtained as shown in Fig.16-Fig.17.

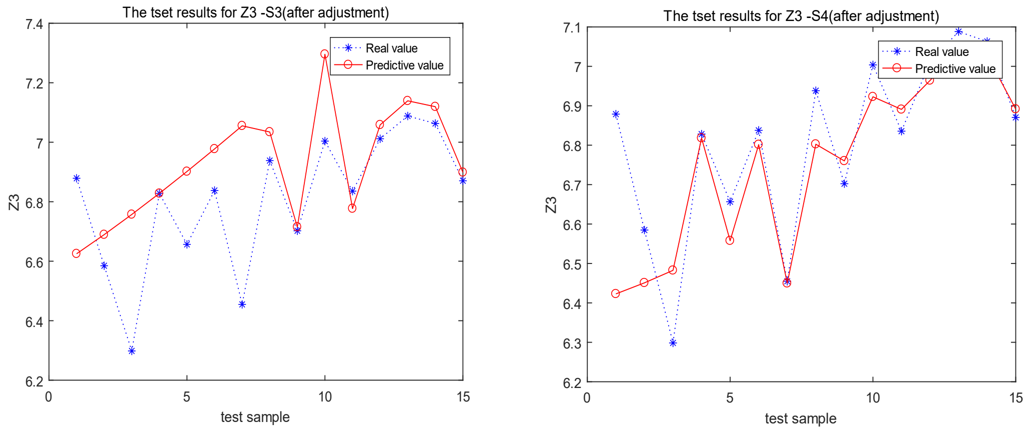

Fig.16 Z_3 Test results after adjusting neural network

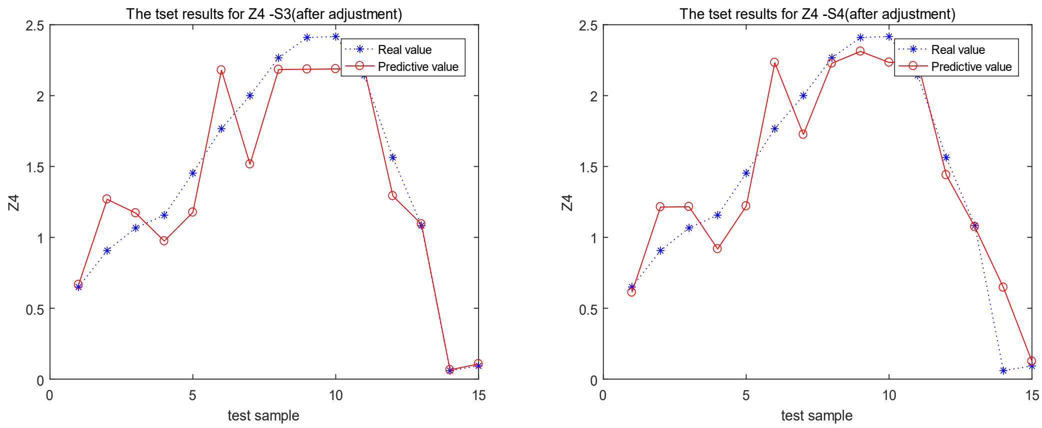

Fig.17 Z_4 Test results after adjusting neural network

6.3.5 Prediction of policy indicators value based on adjusted BP Neural Network

According to the above adjusted BP Neural Network, the subscript of simulation test is changed to: from the beginning of forecast quarter to the end of the last quarter in 2024. After Biden and Trump are elected respectively, the forecast values of each China policy indicator in the next term are shown in Tab.22.

Tab.22 The forecast values of China policy indicators of Biden and Trump

Time	Biden				Trump			
	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4
2020-12	14.4633	146336890	6.8385	0.2059	13.5263	156336890	6.8302	1.1543
2021-03	14.4882	156456400	6.8383	0.2313	13.6396	176456400	6.8492	1.1698
2021-06	14.5121	144233236	6.8381	0.2503	13.7467	184233236	6.8687	1.1847
2021-19	14.5349	166495358	6.8380	0.2644	13.8480	156495358	6.8887	1.1991
2021-12	14.5568	183191879	6.8379	0.2748	13.9436	153191879	6.9093	1.2129
2022-03	14.5777	161708401	6.8378	0.2823	14.0337	161708401	6.9304	1.2261
2022-06	14.5978	163246349	6.8377	0.2878	14.1185	163246349	6.9520	1.2388
2022-09	14.6171	175448432	6.8376	0.2918	14.1983	165448432	6.9742	1.2510
2022-12	14.6357	191955101	6.8375	0.2946	14.2733	161955101	6.9970	1.2627
2023-03	14.6536	180362600	6.8375	0.2966	14.3437	160362600	7.0203	1.2738
2023-06	14.6708	181238900	6.8374	0.2979	14.4097	161238900	7.0442	1.2846
2023-09	14.6875	189538000	6.8374	0.2989	14.4717	169538000	7.0686	1.2948
2023-12	14.7036	186602383	6.8373	0.2995	14.5297	166602383	7.0936	1.3046
2024-03	14.7193	189603459	6.8373	0.2998	14.5840	169603459	7.1191	1.3140
2024-06	14.7345	186645430	6.8373	0.3000	14.6349	166645430	7.1452	1.3230
2024-09	14.7493	192688457	6.8373	0.3001	14.6825	172688457	7.1718	1.3316
2024-12	14.7638	189926522	6.8372	0.3001	14.7271	179926522	7.1991	1.3398

6.3.6 China's economic indicators prediction based on VAR model

Referring to the analysis method of question 1, based on the value of each China policy index predicted by BP Neural Network, the vector autoregressive model (VAR) is used to analyze and obtain the forecast value of China's economic indicators in the next stage.

This paper uses EViews10 software to establish a VAR based prediction model of the impact of U.S. policy on China's economic indicators. The relationship between China's economic indicators TIE and China policy indicators is obtained as shown in formula (17) (the coefficient is kept to two decimal places).

$$\begin{aligned} TIE(t) = &-0.05TIE(t-1) + 0.71TIE(t-2) + 0.17TIE(t-3) \\ &+204.95Z_1(t-1) - 41.65Z_1(t-2) + 991.70Z_1(t-3) \\ &+3.32e-06Z_2(t-1) - 6.52e-05Z_2(t-2) - 2.48e-05Z_2(t-3) \\ &-2322.39Z_3(t-1) + 94.20Z_3(t-2) + 650.02Z_3(t-3) \\ &+458.91Z_4(t-1) + 4266.21Z_4(t-2) - 4856.57Z_4(t-3) + 14255.72 \end{aligned} \tag{17}$$

Similarly, the relationship between China's economic indicator CD and China policy indicators can be obtained, as shown in formula (18).

$$\begin{aligned} CD(t) = &0.24CD(t-1) + 0.30CD(t-2) - 0.01CD(t-3) \\ &+117.14Z_1(t-1) - 50.66Z_1(t-2) - 8.19Z_1(t-3) \\ &-1.92e-06Z_2(t-1) + 4.91e-07Z_2(t-2) - 5.68e-07Z_2(t-3) \\ &+12.35Z_3(t-1) - 186.68Z_3(t-2) + 195.87Z_3(t-3) \\ &-86.57Z_4(t-1) + 328.85Z_4(t-2) - 327.51Z_4(t-3) - 3.36 \end{aligned} \tag{18}$$

By substituting the historical data and the predicted values of policy indicators for China, the forecast results of China's economic indicators are shown in Tab.23 and Fig.18-Fig.19.

Tab.23 The predicted values of various economic indicators for China

Time	TIE（US $100 million）		CD(100 million RMB)	
	Trump	Biden	Trump	Biden
2020-12	6890.357	6890.357	593.4982	593.4982
2021-03	15070.94	15427.69	1026.773	1232.991
2021-06	13969.15	10875.76	1284.623	1181.862
2021-19	14941.54	19357.2	1110.595	1335.361
2021-12	16814.06	15556.93	1176.988	1315.009
2022-03	17328.38	20244.78	1144.608	1337.854
2022-06	19034.96	19559.75	1164.777	1353.997
2022-09	19696.36	21774.07	1163.094	1352.737
2022-12	20679.85	21772.61	1164.28	1352.034
2023-03	21627.96	22182.64	1171.361	1327.306
2023-06	22488.34	22970.27	1177.487	1331.262
2023-09	23364.2	22779.29	1184.669	1314.779
2023-12	23658.52	23206.92	1179.96	1307.527
2024-03	24603.85	23363.15	1187.201	1305.279
2024-06	24552.95	23253.32	1180.906	1294.381
2024-09	25552.26	23714.81	1189.741	1297.796
2024-12	25198.44	23211.23	1181.768	1285.822

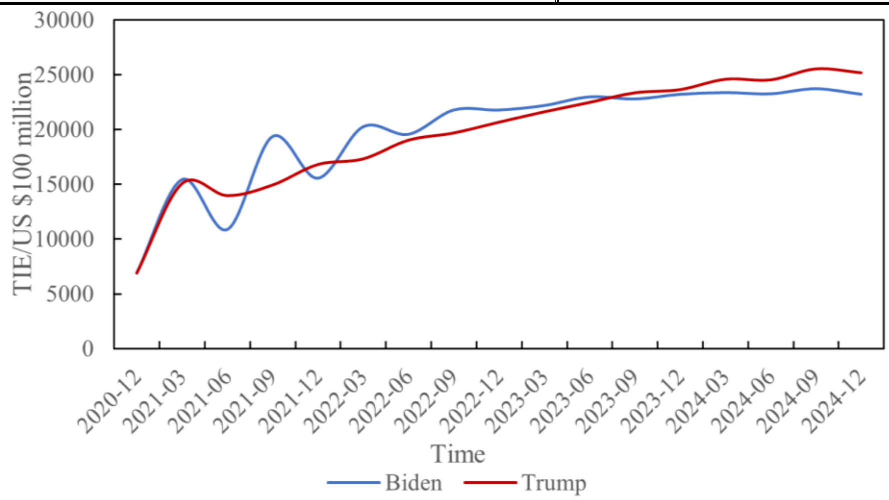

Fig.18 Comparison of TIE prediction results

The analysis of the impact of different candidates on TIE is as follows:

(1) TIE overall change trend

By comparing the overall change trend of China's total trade volume between Biden and Trump during their term of office, we can find that after Biden's election, China's total trade volume tends to be stable after the initial rapid growth, while after Trump's election, it shows a slow growth trend. The reason is that Biden encourages the elimination of trade barriers, while Trump does the opposite.

(2) TIE initial fluctuation

Comparing the total trade volume of China between Biden and Trump at the beginning of his term of office, it can be found that China's total trade volume fluctuated after Biden's election, because the change of policies after the election will have a certain impact on Sino US trade.

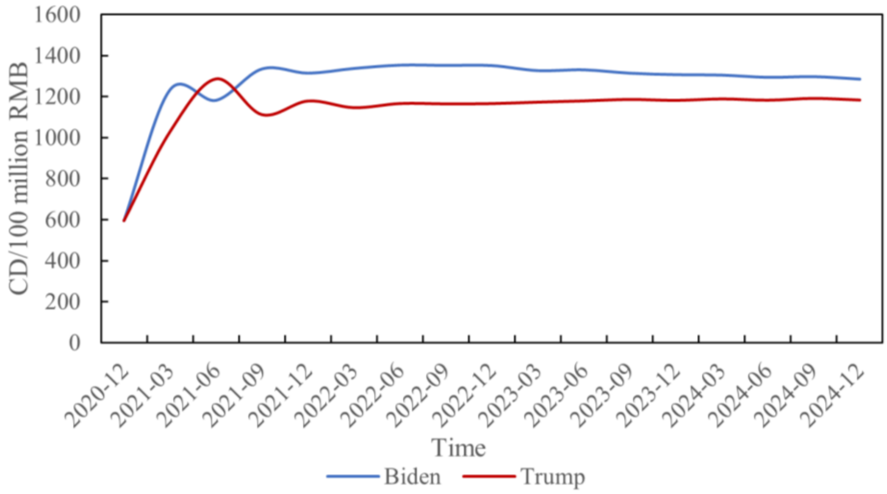

Fig.19 Comparison of CD prediction results

The analysis of the impact of different candidates on CD is as follows:

(1) CD overall stable value

Compared with the general changes of China's tariff revenue after Biden and Trump were elected, the trend of the two changes was almost the same, but the final stable value of Biden was larger, because Biden opposed to continue to impose trade tax on China, so China's tariff revenue rose accordingly after Biden took office

(2) CD later changes

Compared with the change trend of China's tariff revenue at the end of Biden's and Trump's term of office, China's tariff showed a weak downward trend at the end of Biden's term of office, because he exerted trade pressure on China through other channels.

7 Modeling and solution of problem three

7.1 The judgment process of AHP

Based on the basic principle of AHP, this paper first establishes the hierarchical structure model according to the impact of American presidential candidates' policy indicators on China's economy, and then uses different methods to construct the judgment matrix of criteria-layer and scheme-layer and conduct consistency test. Then, the importance of the policies of the two candidates on China's economy is obtained in order of hierarchy, and finally a conclusion is drawn.

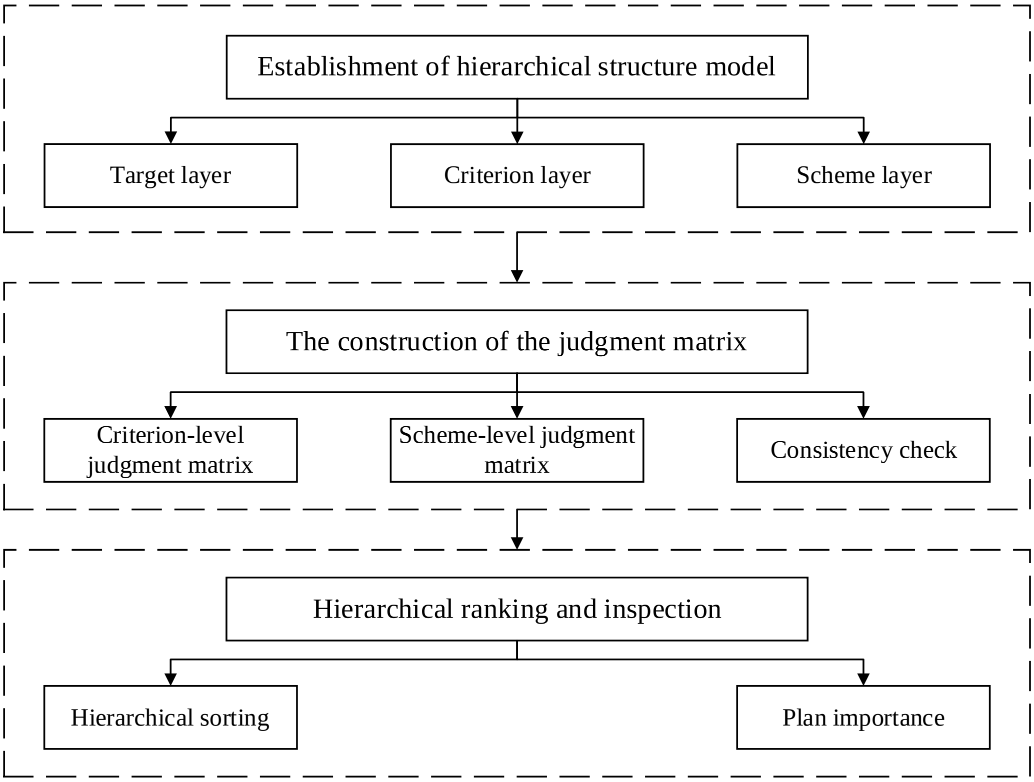

Fig.20 AHP-based process for judging the impact of the US presidential election on China's economy

7.2 Establishment of hierarchical structure model

According to the impact of US presidential candidates' policy indicators on China's economy, a three-layer hierarchical structure model with target layer, criterion layer (10 indicators) and scheme layer (2 schemes) is established, as shown in Fig.21.

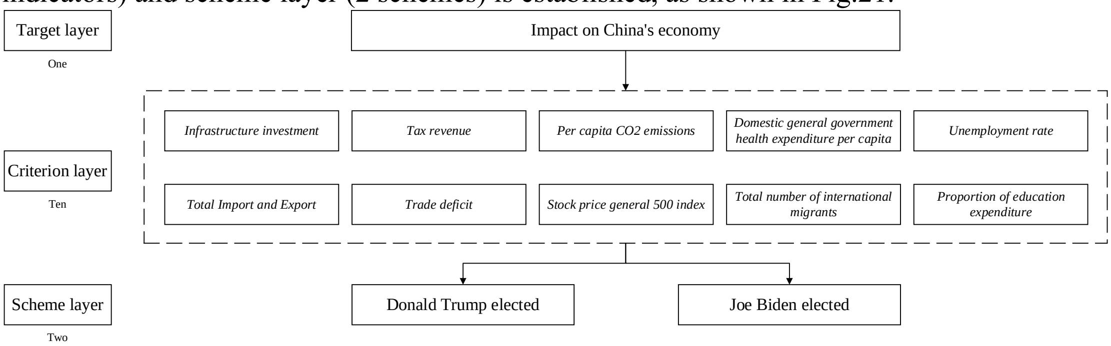

Fig.21 Hierarchical structure model

(1) Target layer

The target layer is the purpose of using AHP, taking the best economic situation of China as the target layer.

(2) Criterion layer

Ten policy indicators affected by the US presidential candidate policy are taken as the standard level indicators, which are infrastructure investment, tax revenue, per capita CO_2 emissions, per capita domestic general government health expenditure, unemployment rate, total import and export, trade deficit, stock price general 500 index, total number of international immigrants and proportion of education expenditure.

(3) Scheme layer

The two major US presidential candidates, namely the election of Trump and the election of Biden.

7.3 The construction of judgment matrix

In AHP, the judgment matrix of each layer represents the relative importance of all indicators of this layer to the corresponding indicators of the upper layer. The hierarchical structure model shown in Fig.21 has three layers: the target layer, the criterion layer and the plan layer. Therefore, there are two types of judgment matrices, namely the criterion layer and the plan layer judgment matrix. Among them, the criterion layer needs to construct a judgment matrix. The layer needs to construct 10 judgment matrices.

(1) The construction of criterion-layer judgment matrix

In order to avoid the shortcomings of highly subjective scoring by experts, this article takes the three principal component forecast data for the next term after Trump and Biden are elected, and then normalizes them as sample independent variables to predict data for China policy indicators. After comprehensive averaging, normalization is used as the sample dependent variable, and the multiple linear regression method is used to construct the criterion-layer judgment matrix. Specific steps are as follows:

1)Data normalization

In order to avoid the influence of different index dimensions on the analysis results, it is necessary to normalize the samples. In this paper, the max normalization method is used, that is to make the indexes of each sample $\overline{Y}_i = \overline{Y}_i^{orig} / \overline{Y}_i^{\max}$, where $\overline{Y}_i^{orig}$ is the original value of index $\overline{Y}_i$ in the sample, $\overline{Y}_i^{\max}$ is the maximum value of index $\overline{Y}_i$ in all samples. Obviously, after normalization, the values of $\overline{Y}_i$ in the sample are all located in [0,1].

2)Multiple linear regression

For the selected independent variable $\overline{Y}_i$ and dependent variable Z ($Z = (\sum Z_i)/3, i = 1,2,3$), use the following equation to perform multiple linear regression:

$$Z = a_0 + a_1\overline{Y}_1 + a_2\overline{Y}_2 + a_3\overline{Y}_3 \tag{19}$$

Then multiply the regression coefficients of the three principal components with the correlation coefficients of the ten policy indicators and sum them to obtain the importance of these ten policy indicators.

Let the principal component expression be

$$\overline{Y}_i = \sum b_{ij} X_j, i = 1,2,3, j = 1,2,...,10 \tag{20}$$

Then the formula for calculating the importance of the ten policy indicators is

$$S_j = \min\left\{ \left\lceil \sum_i a_i b_{ij} \right\rceil, 9 \right\}, i = 1,2,3, j = 1,2,...,10 \tag{21}$$

Finally, the criterion-layer judgment matrix is constructed according to this importance.

(2) The construction of the scheme-layer judgment matrix

In the same way, according to the above method, the importance of ten policy indicators in the case of two presidential candidates being elected respectively is constructed, and the importance of the two is compared to construct a judgment matrix at the scheme-layer.

(3) Judgement matrix construction result

The multiple linear regression equation is as follows

$$Z = 0.27 + 1.36\overline{Y}_1 + 0.69\overline{Y}_2 + 0.05\overline{Y}_3 \tag{22}$$

The importance results of the ten policy indicators are as follows

Tab.24 Importance of policy indicators

Policy indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
Importance	1	3	3	3	3	5	7	9	5	1

The criterion-layer judgment matrix is constructed according to the above-mentioned importance results, and the judgment matrix of the scheme layer can be obtained in the same way. The specific results are shown in Attachment 1.

7.4 Hierarchical ranking and inspection

(1) Hierarchical ranking and inspection steps

Sort the judgment matrices at each layer, calculate the weight vector, and perform consistency testing. To facilitate the introduction of the method, let the currently considered judgment matrix be $A_{n\times n}$, which is a square matrix of order 1, and its elements are a_{ij}.

This paper uses the square root method to calculate the weight vector. The calculation steps are as follows:

1)Find the product of each row element of the judgment matrix M_i

$$M_i = \prod_{j=1}^{n} a_{ij}, \quad i = 1, 2, \ldots, n \tag{23}$$

2)Calculate the n^th^ root of M_i

$$\overline{W_i} = \sqrt[n]{M_i}, \quad i = 1, 2, \ldots, n \tag{24}$$

3)Calculate the weight vector and eigenvalue

$$W_i = \overline{W_i} / \sum_{j=1}^{n} \overline{W_j}, \quad i = 1, 2, \ldots, n \tag{25}$$

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(AW)_i}{W_i} \tag{26}$$

The consistency test method for the judgment matrix A is as follows:

1)Calculate the consistency index

$$C.I. = \frac{\lambda_{\max} - n}{n - 1} \tag{27}$$

2)Find the corresponding average random consistency index, see Tab.25

Tab.25 Consistency Indicator *R.I.*

n	1	2	3	4	5	6	7	8	9	10	11	12
R.I.	0.00	0.00	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54

3)Calculate the agreement ratio

$$C.R. = \frac{C.I.}{R.I.} \tag{28}$$

When $C.R. < 0.1$, the judgment matrix is considered acceptable; when $C.R. \geq 0.1$, the judgment matrix should be revised.

(2) Hierarchical ranking and test results

Tab.26 shows the weight of the influence of the two US presidential candidates on China's economy.

Tab.26 The weight of the elements in the scheme-layer to the decision goal

Options	Weights
Joe Biden elected	0.51
Donald Trump elected	0.49

It can be seen from Tab.26 that the election of Trump or Biden has little difference in the impact of the Chinese economy. Therefore, it is only necessary to analyze the impact of different policies on the Chinese economy without distinguishing specific leaders. The weight ranking of ten policy indicators is shown in Tab.27.

Tab.27 The weight of policy indicators to decision goals

Policy indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
Weights	0.025	0.075	0.075	0.075	0.075	0.125	0.175	0.225	0.125	0.025

It can be seen from the table that the weight of X_8 is the largest, followed by X_7, and X_6. The sum of the three weights accounts for more than 50%. Therefore, this paper mainly analyzes the impact of the policies corresponding to the three indicators on China's economy and puts forward countermeasures.

7.5 The influence of US presidential election results on China's economy and Countermeasures

From the above analysis, it can be concluded that no matter which U.S. presidential candidate is elected, its impact on China's economy is not much different, because Biden and Trump have more consensus than differences on China policy, and both advocate taking a tough attitude towards China. Therefore, for China's economic development, the countermeasures can be similar.

From the weight of policy indicators on China's economy, it can be seen that the Stock price general 500 index has the greatest impact on China's economy, followed by trade deficit and total imports and exports. These indicators mainly correspond to the financial and trade policies of US, and appropriate China's economic policies should be put forward for these policies.

The financial and monetary policies and foreign trade policies of US have a great impact on China's economy, which shows that China's dependence on foreign economy is too strong, which is inseparable from opening up and economic globalization. However, with the sudden change of the international environment, the prevalence of de globalization, the trade war between China and US, the global COVID-19 epidemic continues to break out, and the uncertainty increases.

In the short term, China should improve its market diversification and expand its markets outside US with the help of the "One Belt One Road" initiative. It is possible to further strengthen cooperation with the European Union, East Asia and other regions in the financial, currency and trade fields, expand the scope of cross-border use and cross-border payments of the RMB, and minimize the excessive dependence of monetary policy on the US monetary policy.

From a long-term perspective, China should focus on domestic demand, deepen supply-side structural reforms, and alleviate imbalances and inadequacy in economic development. Effectively change the situation that has been at the low end of the international industrial chain for many years, change the one-sided export that relies solely on commodity trade, and shift to both commodity trade and service trade. With the domestic big cycle as the main body, the domestic and international double cycles promote each other, and accelerate the formation of a new development pattern.

8 Model evaluation and promotion

8.1 Model evaluation

(1) In terms of data sources, this paper selects data from multiple economic databases to ensure reliable and abundant data sources.

(2) In question 1, this paper first interpolates the missing data, and uses Lagrange interpolation to interpolate the missing values, which can improve the quality of data and the accuracy of fitting and prediction in the model. Then, principal component analysis is used to extract the principal components of ten policy indicators, which effectively retains the parameter information of the original policy indicators on the premise that the principal components are independent of each other. Secondly, through the comparative analysis of BP neural network errors of different parameters, the optimal network parameters are determined.

Based on this, the BP neural network which can accurately predict the main component values is established and adjusted according to the impact of epidemic situation. According to the fitting degree between the adjusted data and the test set, the prediction results are reliable. Finally, based on the VAR model, the relationship between the U.S. economic indicators and the principal components is given, and then the predicted values of the U.S. economic indicators in the next four years after the two candidates are elected respectively are obtained. The VAR economic prediction model has been widely used in the economic circles and proved to be reasonable and reliable.

(3) In question 2, this paper adopts the same treatment method as the first one. The main difference lies in the different selection of indicators, which mainly focuses on the selection of indicators for China policy, which conforms to the question hypothesis.

(4) In question 3, the analytic hierarchy process (AHP) model based on multiple linear regression is used to analyze and calculate the influence weight of each policy of the two candidates and their influence on China's economy. Different from the judgment matrix determined by the expert scoring method in the conventional analytic hierarchy process (AHP), this paper analyzes and calculates the policy data of question 1 and the economic data of China in question 2 Meta linear regression, according to the regression coefficient to determine the importance of indicators, and then construct a judgment matrix, to avoid the subjective impact caused by artificial scoring.

8.2 Model promotion

In this paper, BP Neural Network adjustment indicators value fitting and forecasting method based on epidemic situation, the economic prediction model based on VAR and the analytic hierarchy process model based on multiple linear regression can be applied to predict the impact of any two presidents on the economy of China and the United States in the future election.

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Attachment

Attachment 1

Question 1 raw data (data source: the World Economic Database of China Economic Information Network.)

Indicator	Policy indicator										Economic indicator		
Time	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	GDP	PPI	A_GNI
2009-03	107.9592	291705	4.00	854.19	8.80	623600	122000	797.87	13907427	10.88	3598.64	86.18	42572.29
2009-06	107.6463	280858	4.07	929.65	9.13	611700	111300	919.32	11500592	12.40	3588.21	83.82	44406.70
2009-09	108.1524	281105	4.29	949.89	9.60	662300	127700	1057.08	10957104	13.25	3605.08	86.41	45195.36
2009-12	109.7103	290590	4.37	953.17	9.53	718100	142700	1115.10	10932390	13.54	3657.01	86.48	46936.26
2010-03	103.0495	307843	4.38	953.75	10.40	752700	149900	1169.43	10972209	13.52	3680.34	88.20	47982.05
2010-06	104.4826	318291	4.36	954.57	9.47	786400	161600	1030.71	10994386	13.15	3731.52	90.03	48219.81
2010-09	105.5594	327832	4.35	965.45	9.47	810300	165700	1141.20	11045910	12.79	3769.98	92.22	48206.80
2010-12	106.6859	334587	4.36	974.11	9.13	842700	158300	1257.64	11111204	12.65	3810.21	91.23	48902.93
2011-03	103.1794	367183	4.36	976.28	9.50	889800	178600	1325.83	11143363	12.64	3821.46	91.81	49428.12
2011-06	104.5994	371446	4.36	975.87	8.90	921100	182500	1320.64	11147548	12.65	3874.05	92.26	49526.68
2011-09	105.2449	370203	4.23	991.33	9.07	934800	179600	1131.42	11056016	13.02	3897.96	94.60	49484.49
2011-12	106.6262	379195	4.09	1009.37	8.33	944700	184900	1257.60	10948954	13.47	3949.12	94.25	50816.43
2012-03	108.1334	385405	4.03	1016.92	8.63	958600	191200	1408.47	10903053	13.67	4004.94	95.19	52292.41
2012-06	109.0276	392598	4.05	1021.81	8.00	959800	184400	1362.16	10941343	13.69	4038.06	95.82	52878.78
2012-09	109.7358	397587	4.06	1022.27	8.13	951400	175600	1440.67	11015916	13.46	4064.29	97.01	52904.48
2012-12	110.4224	411034	4.06	1021.02	7.50	952000	179000	1426.19	11055516	13.19	4089.72	96.19	53119.84
2013-03	111.8448	430034	4.06	1020.41	8.07	957500	175500	1569.19	11061239	13.07	4142.4	96.95	53243.31
2013-06	112.3060	438405	4.09	1056.23	7.40	958200	173800	1606.28	11058766	13.06	4159.48	97.57	53230.83
2013-09	113.7291	445426	4.13	1089.52	7.33	960000	174600	1681.55	11010122	13.23	4212.19	99.09	53201.40
2013-12	115.3111	451627	4.15	1100.14	6.70	970900	165700	1848.36	10884071	13.44	4270.78	98.38	54355.19
2014-03	115.4558	469701	4.15	1099.56	6.93	982500	181700	1872.34	10801681	13.53	4276.14	99.30	55425.32
2014-06	117.6722	480166	4.11	1098.54	6.10	1001100	186700	1960.23	10784481	13.40	4358.23	100.62	55763.40
2014-09	119.6211	481762	4.07	1135.45	6.17	999700	181300	1972.29	11158829	13.25	4430.41	102.37	55742.70
2014-12	120.4870	485241	4.06	1172.74	5.47	994500	184700	2058.90	11587363	13.19	4462.48	101.73	56730.86
2015-03	121.5230	516906	4.06	1186.12	5.83	955300	187900	2067.89	11765912	13.22	4500.85	101.08	57861.96
2015-06	123.0090	516851	4.00	1204.33	5.30	949200	185600	2063.11	11656775	13.26	4555.89	99.77	58321.11
2015-09	123.8452	514227	3.93	1222.18	5.23	937100	188900	1920.03	11510812	13.28	4586.86	100.97	58343.75
2015-12	124.0569	511043	3.91	1229.45	4.80	910600	183000	2043.94	11457511	13.28	4594.7	98.19	58335.20
2016-03	124.6736	508459	3.91	1229.86	5.20	889100	180100	2059.74	11457726	13.28	4617.54	97.58	58334.96
2016-06	125.9294	518804	3.91	1229.27	4.77	898600	182200	2098.86	11646748	13.25	4664.05	97.40	58323.07
2016-09	127.0442	531188	3.88	1245.50	4.97	918300	183900	2168.27	11840956	13.21	4705.34	99.04	58310.92
2016-12	128.4701	534506	3.83	1262.74	4.53	932300	189100	2238.83	11911860	13.19	4758.15	98.15	58974.07
2017-03	129.8527	557873	3.82	1269.01	4.87	955500	192100	2362.72	11906859	13.19	4809.36	98.73	59850.31
2017-06	130.8099	573078	3.82	1284.82	4.23	955700	198500	2423.41	12251437	13.19	4844.81	99.78	60278.08
2017-09	132.4166	547934.2	3.79	1306.36	4.40	962500	193900	2519.36	12708147	13.27	4904.32	101.01	60269.65

2017-12	134.5812	503537.1	3.74	1318.44	3.90	1013100	207900	2673.61	12925297	13.38	4984.49	101.75	61018.95
2018-03	136.6349	479022.1	3.72	1319.33	4.33	1036400	216000	2640.87	12914293	13.44	5060.55	102.42	62509.12
2018-06	138.7303	494738	3.72	1316.96	3.83	1049000	202800	2718.37	12862428	13.44	5138.16	103.36	63634.60
2018-09	140.0134	532165.4	3.70	1329.87	3.87	1057900	224700	2913.98	13365367	13.40	5185.68	105.83	63799.27
2018-12	141.1414	552266.4	3.65	1354.05	3.57	1060100	228500	2506.85	14299783	13.34	5227.46	105.47	63783.73
2019-03	142.5284	534166.4	3.61	1370.77	3.87	1046800	213600	2834.40	14981057	13.30	5278.83	105.27	64522.58
2019-06	143.9767	495679.6	3.61	1372.07	3.63	1039300	222100	2941.76	15078855	13.29	5332.47	104.42	65956.08
2019-09	145.3972	513835	3.61	1374.24	3.63	1035700	218300	2976.74	14580249	13.30	5385.08	105.98	67061.04
2019-12	146.7950	724876.7	3.58	1393.11	3.53	1018800	200400	3230.78	13701584	13.31	5436.85	104.77	65881.75
2020-03	145.5376	1324264	3.53	1423.60	3.83	992700	189300	2584.59	12885902	13.30	5390.28	103.12	59529.98
2020-06	131.7608	2566670	3.52	1443.84	13.03	794000	217000	3100.29	12800359	13.30	4880.03	89.17	44184.98
2020-09	142.8141	4765984	3.70	1419.29	8.83	838900	213900	3363.00	14336219	13.31	5289.41	98.13	45093.45

Question 2 raw data (data source: Zhonghong statistical database.)

Indicator	China's policy indicators			China's economic indicators		
Time	Z_1	Z_2	Z_3	Z_4	TIE	CD
2009-03	4.09	62085844	6.8360	0.20	4288.00	324.02
2009-06	4.89	70079173	6.8257	0.20	5182.24	333.10
2009-09	5.18	79764321	6.8296	0.13	6115.99	403.73
2009-12	5.23	86436024	6.8273	0.10	6491.53	469.49
2010-03	5.45	78112622	6.8263	0.11	6181.20	482.53
2010-06	5.67	93905264	6.8116	0.16	7366.20	539.69
2010-09	5.58	106607198	6.7577	0.18	7943.21	543.34
2010-12	6.08	106810224	6.6428	0.18	8248.84	461.45
2011-03	5.92	97670404	6.5750	0.14	8012.23	711.46
2011-06	6.16	108800318	6.4782	0.09	9027.32	638.77
2011-09	6.40	119450775	6.3994	0.08	9733.62	667.90
2011-12	6.78	120787627	6.3426	0.08	9644.66	540.81
2012-03	6.67	106733734	6.3003	0.10	8594.54	780.20
2012-06	7.04	124531472	6.3441	0.14	9796.49	662.84
2012-09	6.75	124345462	6.3317	0.12	10027.15	679.44
2012-12	7.20	129267512	6.2314	0.14	10250.67	660.30
2013-03	7.32	118245755	6.2170	0.13	9753.89	565.53
2013-06	7.49	125941779	6.1458	0.10	10217.27	646.57
2013-09	7.63	134942375	6.1233	0.07	10631.22	680.10
2013-12	8.06	141618754	6.0806	0.07	10998.73	756.22
2014-03	7.92	122550141	6.1411	0.06	9648.28	664.57
2014-06	8.09	133914738	6.2370	0.09	10549.80	733.58
2014-09	7.97	148212218	6.1519	0.07	11411.96	744.85
2014-12	7.78	150690967	6.1540	0.07	11420.32	700.19
2015-03	7.89	126258555	6.2397	0.06	9043.02	608.02
2015-06	8.08	140560656	6.2007	0.08	9780.29	643.02
2015-09	8.29	147275828	6.3144	0.08	10314.71	643.08

2015-12	7.90	146462157	6.4033	0.12	10518.53	660.88
2016-03	8.03	112737552	6.5264	0.28	8031.31	540.53
2016-06	8.42	125262241	6.5683	0.30	9247.69	663.22
2016-09	8.52	138436286	6.6627	0.30	9733.20	683.06
2016-12	8.37	148475811	6.8692	0.39	10343.19	716.19
2017-03	8.56	126495358	6.8788	0.65	9007.70	700.02
2017-06	9.04	143246349	6.8282	0.91	10136.30	758.42
2017-09	9.08	155448432	6.6566	1.07	10650.70	778.69
2017-12	8.67	163191879	6.5848	1.16	11432.30	760.87
2018-03	9.02	141708400	6.2984	1.45	10434.14	744.15
2018-06	9.41	160362600	6.4548	1.77	11647.80	709.74
2018-09	9.28	171955100	6.8377	2.00	12317.10	762.20
2018-12	9.85	161238900	6.9382	2.27	11960.70	631.57
2019-03	10.38	119538000	6.7023	2.41	10285.60	623.35
2019-06	10.75	138808700	6.8356	2.42	11348.10	711.00
2019-09	11.18	144448600	7.0631	2.14	11911.40	744.00
2019-12	10.89	137352200	7.0117	1.56	12163.00	740.00
2020-03	10.42	106602383	7.0037	1.08	10930.15	627.21
2020-06	11.18	138051500	7.0882	0.06	10866.50	594.00
2020-09	12.08	167480200	6.8705	0.09	12670.40	707.00

Criterion layer judgment matrix

	1	2	3	4	5	6	7	8	9	10
1	1	1/3	1/3	1/3	1/3	1/5	1/7	1/9	1/5	1
2	1/3	1	1	1	1	3/5	3/7	3/9	3/5	3
3	1/3	1	1	1	1	3/5	3/7	3/9	3/5	3
4	1/3	1	1	1	1	3/5	3/7	3/9	3/5	3
5	1/3	1	1	1	1	3/5	3/7	3/9	3/5	3
6	1/5	3/5	3/5	3/5	3/5	1	5/7	5/9	1	5
7	1/7	3/7	3/7	3/7	3/7	5/7	1	7/9	7/5	7
8	1/9	3/9	3/9	3/9	3/9	5/9	7/9	1	9/5	9
9	1/5	3/5	3/5	3/5	3/5	1	7/5	9/5	1	5
10	1	3	3	3	3	5	7	9	5	1

Biden and Trump's comparison of ten policy indicators

Policy indicator	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
Scale comparison	9	1	1	1	1	1/2	1/3	2	3	1

Attachment 2

code 1: Lagrange interpolation

lagrange_newton_interp.m

```
clc;
clear;
```

```
%Parameter initialization
inputfile=xlsread('C:\Users\Admin\Desktop\DATA.xls',’raw data’);
for i=1:size(inputfile,2)
index=i;
data = inputfile(:,index);
la_data = ployinterp_column(data,'lagrange');    %Call Lagrange for interpolation
%The results are written to a file
rows = size(data,1);
result = cell(rows+1,2);
result{1,1}='original value';
result{1,2}='Lagrange interpolation';
result(2:end,1)= num2cell(data);
result(2:end,2)= num2cell(la_data);
xlswrite('C:\Users\Admin\Desktop\DATA.xls',’after data’);
end
```

ployinterp_column.m

```
function outputdata= ployinterp_column(columndata,type)
nans = isnan(columndata);
notzeroIndexes = find(nans);
%zeroIndexes = find(nans==0);
rows=size(columndata);
%currentValues=zeros(size(zeroIndexes));
for i=1:size(notzeroIndexes)
    pre5=findPre5(notzeroIndexes(i),columndata);
    last5=findLast5(notzeroIndexes(i),rows(1),columndata);
    [~,pre5cols]=size(pre5);
    [~,last5cols]=size(last5);
    if    strcmp(type,'lagrange')
        missingValue=lagrange_interp([1:pre5cols,pre5cols+2:last5cols+pre5cols+1],...
                    [pre5,last5],pre5cols+1);
    end
    columndata(notzeroIndexes(i),1)=missingValue;
end
outputdata=columndata;
end
function pre5=findPre5(index,columndata)
if index<=0
    disp('error');
    exit;
end
num=5;
pre5=nan(1,5);
for i=index-1:-1:1
    if isnan(columndata(i))==0
        pre5(num)=columndata(i);
        num=num-1;
    end
    if num==0
        break;
    end
end
pre5=pre5(~isnan(pre5));
end
```

```
function last5=findLast5(index,rows,columndata)
if index<=0 || index>rows
    disp('error');
    exit;
end
num=0;
last5=nan(1,5);
for i=index+1:rows
    if isnan(columndata(i))==0
        num=num+1;
        last5(num)=columndata(i);
    end
    if num==5
        break;
    end
end
last5=last5(~isnan(last5));
end
```

lagrange_interp,m

```
function [ yi ] = lagrange_interp (X,Y,xi)
n=length(X);
m=length(xi);
yi=zeros(size(xi));
for j=1:m
    for i=1:n
temp=1;
        for k=1:n
            if(i~=k)
                temp=temp*(xi(j)-X(k))/(X(i)-X(k));
            end
        end
        yi(j)=Y(i)*temp+yi(j);
    end
end
end
```

code2: BP neural network

BPmain.m

```
R=zeros(20,N);
I=zeros(20,N);
for i=1:N
    index=i;
    for j=1:20
        num_neurons=i;
        [error,R2,a]=BPTrain(index,num_neurons);
        R(j,i)=R2;
        I(j,i)=a;
    end
end
```

BPTrain,m

```
function [error,R2,a] = BPTrain(index,num_neurons)
```

```
%% Input training set and test set
%Training set 1 (data from Obama's eight years in office)
Train1=xlsread('C:\Users\Admin\Desktop\ExportData.xls',' Training set 1');
%Training set 2 (data from Obama's 8 years + Trump's 4 years)
Train2=xlsread('C:\Users\ Admin \Desktop\ExportData.xls',' Training set 2);
%Test set (data from Trump's four years in power)
Test=xlsread('C:\Users\ Admin \Desktop\ExportData.xls',' Test set    ');
% Prediction set
%PY=xlsread('C:\Users\ Admin \Desktop\ExportData.xls','Sheet2');
%P_Y=PY';
%py=mapminmax('apply',P_y,ps_input);
%Training set and Test set selection
P_train=Train2(:,1)';
T_train=Train2(:,index)';
P_test=Test(:,1)';
T_test=Test(:,index)';
%Data normalization
[p_train, ps_input]=mapminmax(P_train,0,1);
[t_train, ps_output] = mapminmax(T_train,0,1);
p_test = mapminmax('apply',P_test,ps_input);
%Neural network creation
net=newff(P_train,T_train,num_neurons); %Number of hidden neurons
%Set training parameters
net.trainParam.epochs=1000; %Number of iterations
net.trainParam.goal=1e-3; %Training objectives
net.trainParam.lr=0.01; %Learning rate
%Training network
[net,tr]=train(net,p_train,t_train);
%Simulation test
t_sim=sim(net,p_test);
% t_sim=sim(net,py);
%Data inverse normalization
T_sim=mapminmax('reverse',t_sim,ps_output);
%%Performance evaluation
%Relative error
error=abs(T_sim-T_test)./T_test;
%Coefficient of determination R²
    R2=(size(T_test,2)*sum(T_sim.*T_test)-sum(T_sim)*sum(T_test))^2/((size(T_test,2)*sum((T_sim).^2)-
    (sum(T_sim))^2)*(size(T_test,2) * sum((T_test).^2)-(sum(T_test))^2));
%Comparison of results
result=[T_test' T_sim' error'];
%Number of iterations
a=tr.num_epochs;
end
```

code3: VAR model prediction

VAR_GDP.m

```
BG=xlsread('C:\Users\ Admin \Desktop\predicted data.xlsx','Sheet1');
for i=1:size(BG,1)
        BG(i+2,5)=(-0.45*BG(i+1,5)+0.84*BG(i,5)+259.10*BG(i+1,2)-
    102.19*BG(i,2)+3.02*BG(i+1,3)-11.09*BG(i,3)-142.00*BG(i+1,4)+37.25*BG(i,4)+2745.08);
end
```

VAR_PPI.m

```
BP=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet2');
```

```
for i=1:size(BP,1)
    BP(i+3,5)=(-0.34*BP(i+2,5)+0.04*BP(i+1,5)+0.35*BP(i,5) ...
              +5.71*BP(i+2,2)-6.25*BP(i+1,2)+1.95*BP(i,2) ...
              -0.83*BP(i+2,3)+3.42*BP(i+1,3)-1.83*BP(i,3) ...
              -10.85*BP(i+2,4)-2.75*BP(i+1,4)+5.62*BP(i,4)+90.23);
End
```

VAR_A_GNI.m

```
BGN=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet3');
for i=1:size(BGN,1)
BGN(i+5,5)=(0.87*BGN(i+4,5)-1.17*BGN(i+3,5) -1.52*BGN(i+2,5)+0.15*BGN(i+1,5)+1.10*BGN(i,5) ...
    +8951.40*BGN(i+4,2)-6076.37*BGN(i+3,2)+3514.18*BGN(i+2,2)-
1322.38*BGN(i+1,2)+821.06*BGN(i,2) ...
    -4080.84*BGN(i+4,3)+3168.15*BGN(i+3,3)-1250.89*BGN(i+2,3)+1233.70*BGN(i+1,3)-
1304.08*BGN(i,3) ...
-7473.31*BGN(i+4,4)-4625.25*BGN(i+3,4)+10934.90*BGN(i+2,4)-4265.30*BGN(i+1,4)-6841.72*BGN(i,4)
+85461.9);
end
```

VAR_TIE.m

```
BTIE=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet4');
for i=1:size(BTIE,1)
BTIE(i+3,6)=- 0.045*BTIE(i+2,6)+ 0.71*BTIE(i+1,6)+ 0.17*BTIE(i,6) ...
          + 204.95*BTIE(i+2,2)- 41.65*BTIE(i+1,2)+ 991.70*BTIE(i,2) ...
          +3.32e-06*BTIE(i+2,3)-6.52e-05*BTIE(i+2,3)- 2.48e05*BTIE(i,3) ...
          - 2322.39*BTIE(i+2,4)+ 94.20*BTIE(i+1,4)+ 650.02*BTIE(i,4) ...
          +458.91*BTIE(i+2,5)+4266.21*BTIE(i+1,5)-4856.57*BTIE(i,5)+14255.72;
end
```

VAR_CD.m

```
BCD=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet4');
for i=1:size(BCD,1)
BCD(i+3,6)= 0.24*BCD(i+2,6)+ 0.30*BCD(i+1,6)- 0.01*BCD(i,6) ...
          + 117.14*BCD(i+2,2)- 50.66*BCD(i+1,2)- 8.19*BCD(i,2) ...
          -1.92e-06*BCD(i+2,3)+4.91e-07*BCD(i+2,3)-5.69e-07*BCD(i,3) ...
          + 12.35*BCD(i+2,4)- 186.68*BCD(i+1,4)+ 195.87*BCD(i,4) ...
          - 86.57*BCD(i+2,5)+ 328.85*BCD(i+1,5)- 327.51*BCD(i,5)- 3.36;
end
```

code4: multiple linear regression

```
clc
clear
X=xlsread('C:\Users\Admin\Desktop\datah.xlsx','Sheet1','Q19:S28');
X=[ones(size(X,1),1),X];
Y=xlsread('C:\Users\Admin\Desktop\datah.xlsx','Sheet1','S33:S42');
[b,bint,r,rint,stats]=regress(Y,X);
b,bint,stats
rcoplot(r,rint)
z=b(1)+b(2)*X(1,:)+b(3)*X(2,:)+b(4)*X(3,:);
plot(X,Y,'k+',X,z,'r')
xlswrite('C:\Users\Admin\Desktop\datah.xlsx',b,'Sheet2,'A3')
xlswrite('C:\Users\Admin\Desktop\datah.xlsx',bint,'Sheet2','B3')
xlswrite('C:\Users\Admin\Desktop\datah.xlsx',stats,'Sheet2','D3')
```

code5: AHP

AHP.m

```
function [Q]=AHP(B)
```

```
% Q is the weight and B is the contrast matrix
[n,m]=size(B);
%The discriminant matrix has complete consistency
for i=1:n
    for j=1:n
        if B(i,j)*B(j,i)~=1
        fprintf('i=%d,j=%d,B(i,j)=%d,B(j,i)=%d\n',i,j,B(i,j),B(j,i))
        end
    end
end
%Find the eigenvector corresponding to the largest eigenvalue
[V,D]=eig(B);
tz=max(D);
tzz=max(tz);
c1=find(D(1,:)==max(tz));
tzx=V(:,c1);
quan=zeros(n,1);
for i=1:n
quan(i,1)=tzx(i,1)/sum(tzx);
end
Q=quan;
CI=(tzz-n)/(n-1);
RI=[0,0,0.58,0.9,1.12,1.24,1.32,1.41,1.45,1.49,1.52,1.54,1.56,1.58,1.59];
CR=CI/RI(1,n);
if CR>=0.1
   fprintf('Did not pass the consistency test \n');
else
  fprintf('Pass the consistency test \n');
end
```