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Analysis of the Economic Impact of the US Presidential Candidates on the United States and China

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Abstract: *In order to analyze the possible impact of the election of different candidates in the U.S. general election on the U.S. economy and the Chinese economy, and put forward economic countermeasures and policy recommendations in related fields in China, this paper applies two models, Time Series Model and BP Neural Network.*

Keywords: *GDP; Time Series Model; BP Neural Network*

1. Introduction

The 2020 US general election has attracted the attention of people from all over the world. Republican candidate Donald Trump and Democratic candidate Joe Biden were competing for president. They have different political stands and administrative programs in finance and trade, economic and financial governance, and other key development areas.

President Trump believes that US interests are above all else, and aims to increase the income of enterprises and high-income groups. In terms of diplomacy, he prefers to use tariff restrictions and develop against globalization. Biden attempts to increase tax of high-income groups and escalate income tax rates. His style of foreign diplomacy is more moderate and open. Though he attempts to incline to multilateralism, he repairs relations with allies to restricting China.

2. Time Series Model

2.1 Model Background

Due to lack of data, we choose time series model, including ARIMA, auto regression and 2nd auto regression. Time series analysis refers to the theory and method of establishing mathematical models through curve fitting and parameter estimation based on the time series data obtained from systematic observations, which is often used in the macro analysis of the national economy [1]. The main purpose of time series analysis is to predict the future based on existing historical data [2]. We will use ARIMA (p,d,q), short for Autoregressive Integrated Moving Average, and the AR(p), known as Autoregressive Model, in the time series model.

ARIMA is a forecasting algorithm that explain the time series using its own past data which is its lags and lagged forecast errors, thus predicting the future values. An ARIMA model is characterized by 3 terms: p, d, q. Here p,d,q respectively refers to the order of the AR term, the order of the MA term and the number of differencing required to make the time series stationary [2].

A pure Auto Regressive (AR only) model is one where Y_t depends only on its own lags. That is, Y_t is a function of the 'lags of Y_t'

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \,..\, + \beta_p Y_{t-p} + \epsilon_1$$

where Y_{t-1} is the lag1 of the series, β_1 is the coefficient of lag1 estimated by the model, and α is the intercept term that the model estimates.

Furthermore, the equation of ARIMA model is

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$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \,..\, + \beta_p Y_{t-p}\epsilon_t + \phi_1\epsilon_{t-1} + \phi_2\epsilon_{t-2} + .. + \phi_q\epsilon_{t-q}$$

2.2 The Foundation of Model

(1) Convert data set to time series format

(2) Mapping and analyzing data to determine the stationarity. Stationarity means that the fitting curve obtained from the sample time series can continue to follow the existing shape inertia for a period of time in the future. Stationarity requires that the mean and variance of the series do not change significantly. It can be done by tree methods including, testing the sequence diagram, the autocorrelation coefficient and partial correlation coefficient, and the unit root.

(3) Determine p, d, q. Firstly, by observing the graphical representation to determine the order of difference d. Secondly, obtain the autocorrelation coefficient ACF and partial autocorrelation coefficient PACF for stationary time series, and obtain the best level p and order q by analyzing the autocorrelation graph and partial autocorrelation graph.

ACF (autocorrelation function):

$$ACF(k) = \rho_k = \frac{Cov(y_t, y_{t-k})}{Var(y_t)}$$

where *k* represents the number of lag periods, if k=2, it means yt and yt-2.

PACF (partial autocorrelation function) explains the linear correlation between time series observations and their past observations under the condition that the intermediate forecast value is given.

(4) Fit model and make predictions

2.3 Solution and Result

We search for a series of data, including the Gross Domestic Product (GDP), government expenditure (g), average disposable income (*dy*), fixed asset investment (K), net export (NX), unemployment rate, public debt (in billion U.S. dollars), and surplus or deficit (in trillion U.S. dollars) of U.S. and Gross Domestic Product, government expenditure, average disposable income, fixed asset investment, net export, number of high tech enterprises, and Chinese actual use of US foreign direct investment of P.R.C. and analyze it(here all the GDP means the nominal Gross Domestic Product).

Mentioned that for the sake of research, in our paper, the components of U.S. Gross Domestic Product (GDP_{us}) include government expenditure (g_{us}), average disposable income (d_{Yus}), fixed asset investment (K_{us}), net export (NX_{us}), unemployment rate, public debt, and surplus or deficit, and the components of P.R.C. Gross Domestic Product (GDP_{cn}) include government expenditure (g_{cn}), average disposable income (d_{Ycn}), fixed asset investment (K_{cn}), net export (NX_{cn}), number of high-tech enterprises, and Chinese actual use of US foreign direct investment. After statistical analysis of data, we got a series of data including the minimum, maximum, mean, standard deviation, variance, skewness and kurtosis of U.S. and P.R.C. GDP in last decade and its' components. Here is the descriptive statistics:

Table 1: Descriptive statistics of U.S. data [3]

	N	Minimum	Maximin	Mean	Standard Deviation	Variance	Skewness	Standard Error	Kurtosis	Standard Error
GDP_{us}	20	10252.3	21429	15270.975	3338.42531	11145083.56	0.207	0.512	-0.86	0.992
g_{us}	20	1789	4595.3	3248.68	936.8253	877641.585	-0.19	0.512	-1.453	0.992
d_{Yus}	20	33568	45579	38770.55	3327.669	11073381	0.451	0.512	-0.361	0.992
K_{us}	20	30961.7	70742.1	50506.17	11754.8708	138176987.2	-0.077	0.512	-0.823	0.992
NX_{us}	20	-872040.8	-411899	-687358.08	143482.4904	20587225040	0.74	0.512	-0.676	0.992
UR_{us}	20	3.68	9.63	5.883	1.82511	3.331	0.936	0.512	-0.234	0.992
CP_{us}	20	18490	20802	19740.1	716.997	514084.832	0.027	0.512	-1.113	0.992
PD_{us}	20	5674.18	22719.4	13021.946	5770.71085	33301103.73	0.21	0.512	-1.465	0.992
SD_{us}	26	-1.41	0.24	-0.6254	0.42401	0.18	0.008	0.456	-0.372	0.887

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Table 2: Descriptive statistics of P.R.C. data [4]

	N	Minimum	Maximin	Mean	Standard Deviation	Variance	Skewness	Standard Error	Kurtosis	Standard Error
GDP_{cn}	20	99066.1	990865.1	440637.145	288423.8214	83188300763	0.485	0.512	-1.024	0.992
g_{cn}	20	15886.5	238858.37	100827.9785	74709.28105	5581476675	0.494	0.512	-1.179	0.992
TE_{cn}	20	32917.73	645675	294281.4815	228029.3997	51997407114	0.353	0.512	-1.541	0.992
K_{cn}	20	1865.26	36830.73	15807.7065	10972.12857	120387605.3	0.315	0.512	-0.883	0.992
NX_{cn}	19	9758	33573	22547.32	7622.954	58109428.78	-0.41	0.524	-1.073	1.014
d_{Ycn}	20	3721.3	30732.85	13945.067	8748.06036	76528559.99	0.531	0.512	-1.031	0.992
$CUUI$	20	208889	542392	310486.85	88347.54	7805287842	1.348	0.512	1.071	0.992
$RUER$	20	614.28	827.84	719.725	83.62039	6992.369	0.3	0.512	-1.689	0.992

Firstly, by using the time series model to analyze U.S. government expenditure, average disposable income and fixed asset investment from 2000 to 2019, and U.S. net export from 2009 to 2019, we get the time series diagrams. Firstly, the time series diagram of U.S. government expenditure (see Figure 1) rises smoothly, so we decide to use the ARIMA (0,1,0) model to analyze it, and we get time series predictions of g in 2020[3], which is 4586.9(4287.1,4886.7) billion dollars. Secondly, the time series diagram of U.S. average disposable (see Figure 2) income rises smoothly as well, so we determine to use the ARIMA (0,1,0) model to analyze it, and we get time series predictions of d_{yus} in 2020, which is 46211 (44990, 47432) dollars. Thirdly, the time series diagrams of U.S. fixed asset investment (see Figure 3) have an overall trend of rising, but there is a large fluctuation in the middle, so we decide to use the Brown model. Then we get the time series predictions of k_{us} in 2020, that is 73303.8 (71235.6, 75372.1) billion dollars. Fourthly, the time series diagrams of U.S. net export (see Figure 4) has an overall trend of rising as well, but there remain two periods of large fluctuation in the middle, so we determine to use the Brown model to analyze it. Thus, we get the time series predictions of NK_{us} in 2020, that is 1624.411 (1413.4153, 1835.4067) billion dollars. Then we decompose them to eliminate trend components to obtain random residual components[4].

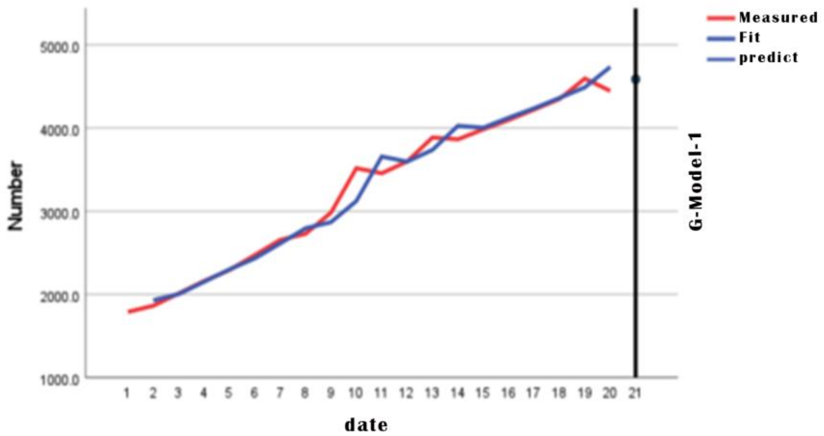

Figure 1: The time series diagrams of U.S. government expenditure

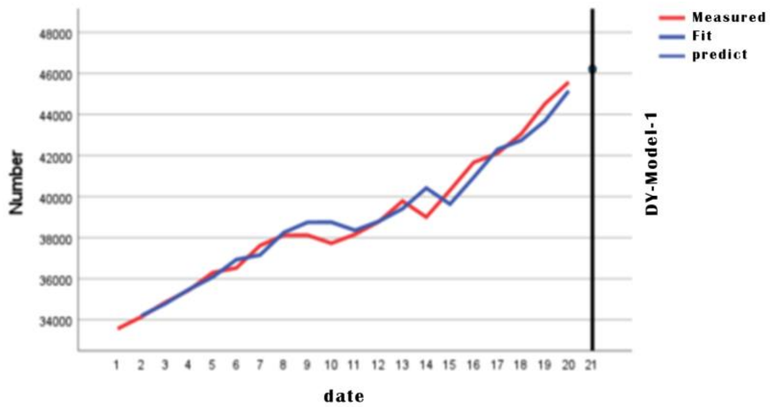

Figure 2: The time series diagrams of U.S. average disposable income

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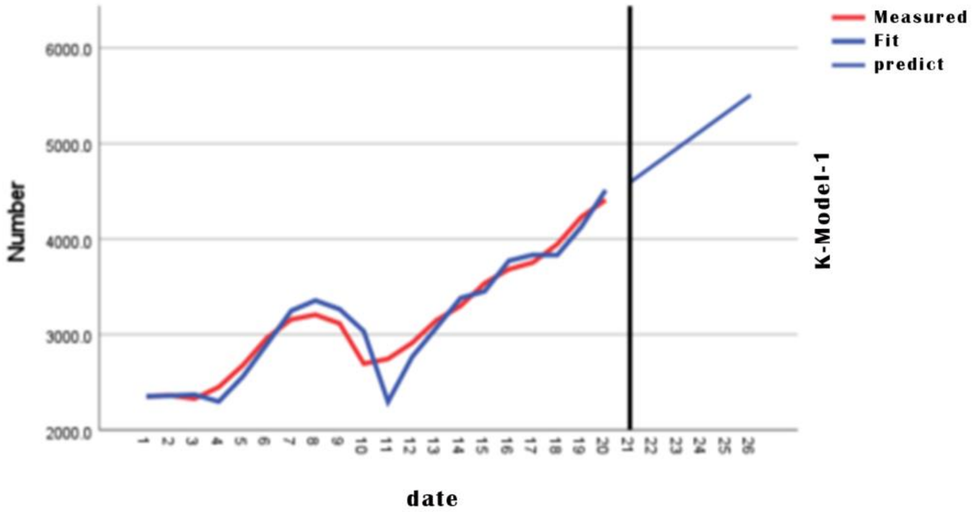

Figure 3: The time series diagrams of U.S. fixed asset investment

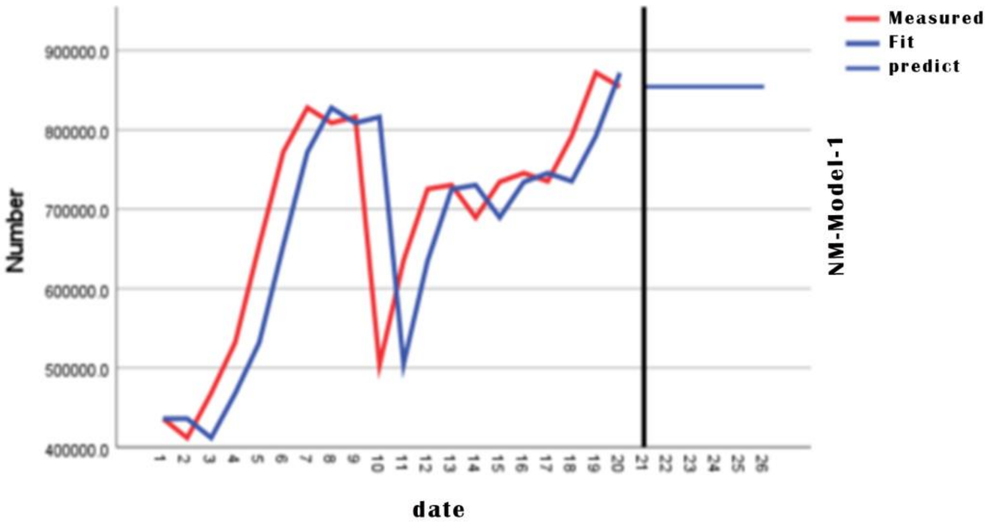

Figure 4:The time series diagrams of U.S. net export

Then, we get the residual diagrams of our models. Firstly, in the residual diagram of ARIMA (0,1,0) model for g_{us} (see Figure 5), the value of Ljung Box(Q) DF is 18 and the index of outliers is zero. Also, all the points in the PACF residuals fall in the middle of a horizontal band. So, our use of ARIMA (0,1,0) model for g_{us} is right and the prediction is reasonable. Secondly, in the residual diagram of ARIMA (0,1,0) model for d_{yus} (see Figure 6), the value of Ljung Box(Q) DF is 18 and the index of outliers is zero. Also, the autocorrelation value does not exceed the boundary value. So, our use of ARIMA (0,1,0) model for d_{yus} is right and the prediction is reasonable. Thirdly, in the residual diagram of Brown model for k_{us} (see Figure 7), the value of Ljung Box(Q) DF is 17, the stationary R-square is zero and the index of outliers is zero. Also, the autocorrelation value does not exceed the boundary value. So, our use of Brown model for k_{us} is right and the prediction is reasonable. Fourthly, in the residual diagram of Brown model for NK_{us} (see Figure 8), the value of Ljung Box(Q) DF is 17, the stationary R-square is -0.055 and the index of outliers is zero. Also, the autocorrelation value does not exceed the boundary value. So, our use of Brown model for NK_{us} is right and the prediction is reasonable.

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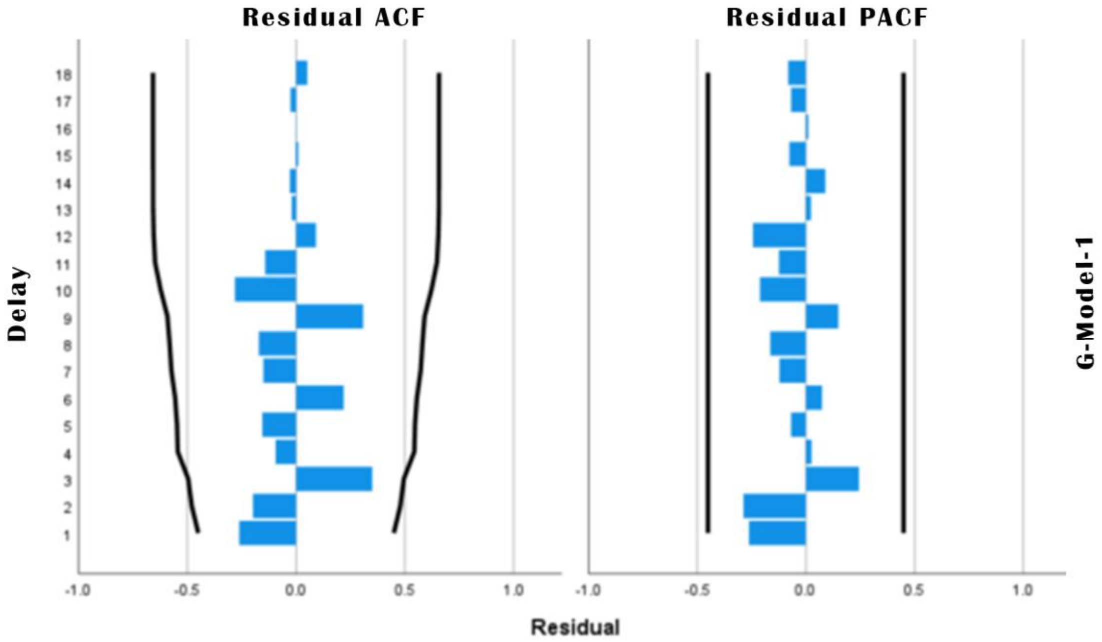
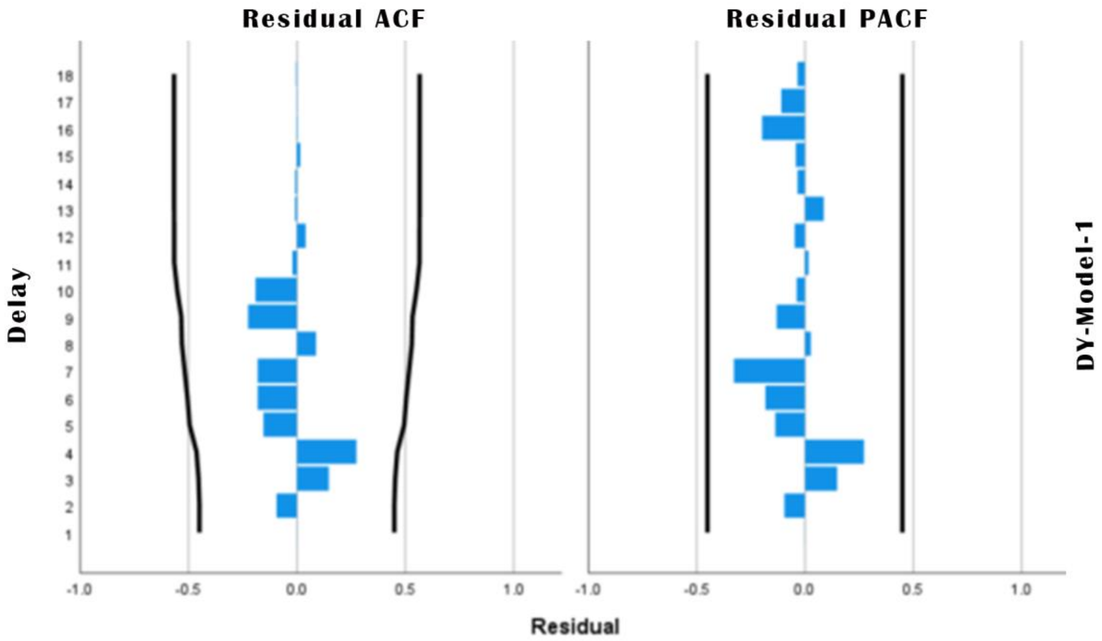


Model statistics						
		Model fit statistics	Young Box Q (18)			
Model	Number of predictors	Smooth R-square	statistics	DF	Significance	Number of outliers
G-model-1	0	7.77E-16	19.859	18	0.341	0

Figure 5: Residual diagram of ARIMA (0,1,0) model for g



Model statistics						
		Model fit statistics	Young Box Q (18)			
Model	Number of predictors	Smooth R-square	statistics	DF	Significance	Number of outliers
DY-model-1	0	1.11E-16	9.647	18	0.943	0

Figure 6 Residual diagram of ARIMA (0,1,0) model for dy

In addition, by using the time series model, we get the time series diagrams of unemployment rate, public debt (in billion U.S. dollars), and surplus or deficit (in trillion U.S. dollars) of U.S. As we can see, the time series diagrams of U.S. unemployment rate from 2000 to 2019 has a small fluctuation and

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then a sharp rise and then a sharp fall, so we decide to use ARIMA (1,1,0) model to analyze it, and we get the prediction of U.S. unemployment rate in 2020, which is 3.52(0.06,6.98). The residual diagram shows that Ljung Box(Q) DF is 17, the stationary R-square is 0.259 and the index of outliers is zero. Also, the autocorrelation value does not exceed the boundary value. Secondly, the time series diagrams of U.S. public debt from 2000 to 2019 rises steadily, so we decide to use Brown model to analyze it, and we get the prediction of U.S. public debt in 2020, which is 25059.29 (23366.7, 26751.89). The residual diagram shows that Ljung Box(Q) DF is 17, the stationary R-square is 0.206 and the index of outliers is zero.

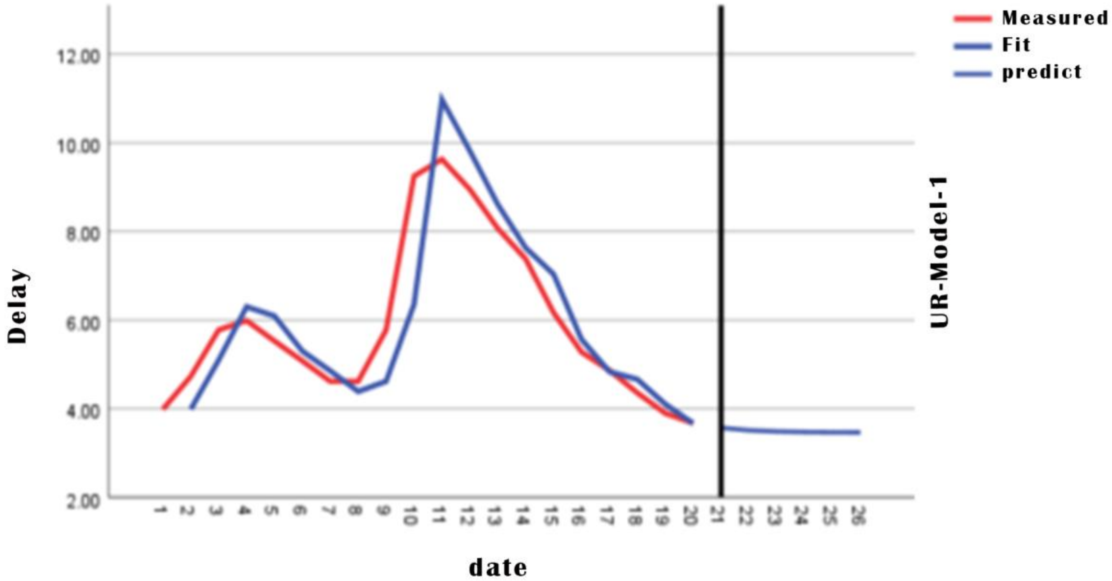
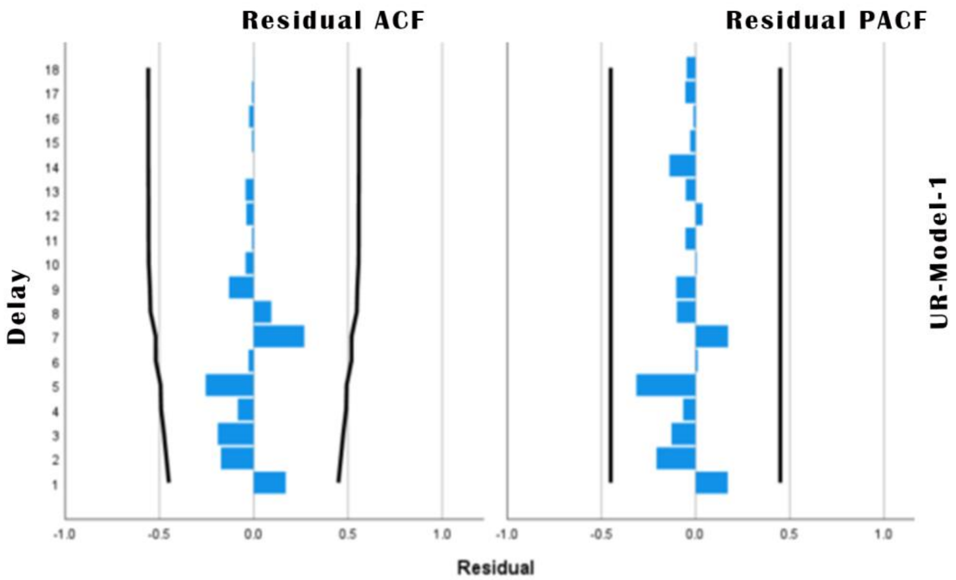


Figure 7 Time series diagrams of U.S. unemployment rate



Model statistics						
		Model fit statistics	Young Box Q (18)			
Model	Number of predictors	Smooth R-square	statistics	DF	Significance	Number of outliers
UR-model-1	0	2.59E-01	8.119	17	0.964	0

Figure 8 Residual diagram of U.S, unemployment rate

Secondly, by using the time series model to analyze P.R.C. government expenditure (*g*), average disposable income (*dy*), fixed asset investment (*K*), net export (*NK*), number of high-tech enterprises, Chinese actual use of US foreign direct investment, and Total retail sales of consumer goods, we get the time series diagrams.

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(1) As we can see, the time series diagrams of P.R.C. government expenditure (*g*) from 2000 to 2019 rises smoothly, so we decide to use the Holt model to analyze it, and we get the prediction of P.R.C. government expenditure (*g*) in 2020, which is 255587.39(247711.36, 263463.42). The residual diagram shows that Ljung Box(Q) DF is 16, the stationary R-square is 0.355 and the index of outliers is zero. Also, the autocorrelation value does not exceed the boundary value.

(2) The time series diagrams of P.R.C. fixed asset investment from 2000 to 2019 rises smoothly, but falls recently, so we use Brown model to analyze it, and we get the prediction, that is 663421.45(77542.82, 749299.99). The residual diagram shows that Ljung Box(Q) DF is 17 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value. However, it is not correct to forecast the fixed assets according to the traditional sequence model. The investment decline in the short term is predicted to continue to decline under the model, but it is easily affected by external factors. Considering the investment of fixed assets, outliers need to be detected, so we need to detect outliers when making time series diagram, so we can get the following correct prediction image and residual diagram .

(3) The time series diagrams of P.R.C. net export (*NK*) from 2000 to 2019 has a trend of rising, but it has two periods of large fluctuation, so we decide to use the ARIMA (0,1,0) model to analyze it, and we get the prediction of *NK* in 2020 is 32041.44 (16671.96, 47410.92). The residual diagram shows that Ljung Box(Q) DF is 18 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value.

(4) The time series diagrams of P.R.C. number of high-tech enterprises (TE) from 2000 to 2019 has a trend of rising, but it has one period of fluctuation, so we decide to use ARIMA (0,1,0) model, and we get the prediction of P.R.C. number of high-tech enterprises in 2020, that is 36219 (29094, 43344). The residual diagram shows that Ljung Box(Q) DF is 0, the stationary R-square is 0.889 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value.

(5) The time series diagrams of P.R.C. average disposable income (*dy*) from 2000 to 2019 rises smoothly, so we decide to use ARIMA (2,2,0) model, and we get the prediction of *dy* in 2020, which is 38846.14 (37509.91, 40182.37). The residual diagram shows that Ljung Box(Q) DF is 0, the stationary R-square is 0.355 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value.

(6) The time series diagrams of Chinese actual use of US foreign direct investment (CUUI) from 2000 to 2019 remains a trend of falling, and has various periods of fluctuation, so we decide to use simple time series model, and we get the prediction, that is 268363 (164784, 371941). The residual diagram shows that Ljung Box(Q) DF is 17, the stationary R-square is 0.012 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value.

(7) The time series diagrams of total retail sales of consumer goods from 2000 to 2019 rises smoothly, so we use Holt model, and we get the prediction, that is 434512.7 (423018.8, 446006.7). The residual diagram shows that Ljung Box(Q) DF is 16, the stationary R-square is 0.282 and the index of outliers is zero. Also, the autocorrelation value roughly does not exceed the boundary value.

2.4 Strength and Weakness

Like any model, the one present above has its strengths and weaknesses. Some of the major points are presented below.

Strengths:

(1)The model is very simple, only endogenous variables are needed and no other exogenous variables are needed.

Weaknesses:

(2)The time series data is required to be stable (stationary), or stable after being differentiated (differencing). Therefore, we need to ensure that the data has no trend and no seasonality.

(3)In essence, it can only capture linear relationships, but not nonlinear relationships. Thus, when predicting GDP, which is usually affected by many external factors, we need to use other models, such as neural network models\

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3. Conclusion

In conclusion, this paper manages to use Time Series Model and BP Neural Network to quantify the likely impact of the election of Trump and Biden on the U.S. and P.R.C. economies, and put forward the economic countermeasure and policy suggestion to relevant fields of China.

For Chinese and American economies, Trump and Biden will bring both positive and negative impacts to them, but relatively speaking, Biden has a more positive impact on the economies of the two countries. We further make suggestions to China's Economic Countermeasures and Policies in Related Areas in Both Cases In conclusion.

For China, China should stick to Chinese characteristics multilateral foreign policy, actively engage in economic cooperation with friendly countries, deepen reform and opening up, and strictly abide by the Five Principles of Peaceful Coexistence.

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